PHD

Introducing technological innovations: Essays on the effects on voting and mental health
(Alternative Format Thesis)

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Introducing technological innovations: Essays on the effects on voting and mental health

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Summary

Recent technological innovations, such as artificial intelligence (AI) and robotics, have attracted much scholarly attention, though largely in respect of their effect on the labour market. The thesis documents the indirect impact of technological innovations on the mental health and voting decisions of workers in the United States. The first paper investigates whether AI can be served as a general-purpose technology, examining comprehensive data of AI patents. It emerges that the stocks of AI related patents, such as deep learning and logistics systems, grow more quickly than robotics ones. AI applications are more popular in the chemical and medical sectors than those of computer science and electronics. The findings of the first paper indicate the potential of AI to serve as a general-purpose technology. Thus, policy makers should consider the readiness of our labour market, political and educational institutions to adjust to the introduction of AI.

The second paper empirically explores the impact of industrial robots on voting outcomes in the U.S. presidential and congressional elections. It studies industrial robot and election data from the United States; the endogeneity issue is addressed by using the European robot usage as the instrument of U.S. robot exposure. It is deduced that industrial robots significantly influence voting behaviour. As such, politicians might seek to mitigate the sway of robots to safeguard political stability.

The third paper empirically assesses how industrial robots affect the mental health of U.S. workers. Statistics of mortalities caused by drug and alcohol abuse, among others, are used as indicators of worker mental health. Industrial robots are found to exert a stark, negative effect on the mental health of workers, reflected by a rising drug and alcohol-induced mortality rate, for example. In other words, increasing robot usage leads to deterioration in mental health. Companies seeking to widen the participation of robotics should take this into account. Likewise, policy makers should provide better protection and welfare for those workers at risk of job loss due to technological advancement.

Overall, we confirm the potential for AI to reach far and wide across our economy. Furthermore, the ability of industrial robots to affect election results and the mental health of individuals is evidenced. Accordingly, it is pivotal that policy makers are prepared for the expansion of AI and able to identify and nullify the possible risks.

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Chapter 1

Introduction

1.1 Research Background

In recent years, artificial intelligence (AI) and robotics have noticeably improved. AI, for instance, is increasingly capable of translation and voice-recognition, the Electronic Frontier Foundation (EEF) observes. AI acts more like humans than ever before. AI is able to imitate intelligent humans to finish tasks in different environment and it acts more like humans. The progress of AI brings likely benefits to production, such as accelerate economic growth and increase income share by replacing human capitals in production. AI could shorten the computing time and facilitate the technological learning in firms and industries. It could also create new tasks that are never exist before, such as flying drones and self-driving cars.

However, the objected increase in poductivity is yet to be observed. Brynjolfsson et al. (2018) propose that full application and adoption of these new technologies is a long-term process, especially given their general-purpose nature. This explanation prompts us to think about the characteristics of AI and whether is can be served as a general-purpose technology. AI, in so far as it can expedite productivity and growth, will affect employment. Above all else, the spread of AI provokes fear of redundancy amongst employees. Sceptics even prognosticate the loss of all human jobs to technology. And yet, though the developments in this field are rapid, the loss of comparative advantages for human workers will be gradual. In particular, workers with low skills are the most vulnerable people that will be replaced by new technologies. Though AI can create some new jobs and assuage labour demand, these benefits do not offset the threat it poses to human workers (Acemoglu and Restrepo, 2018). That being said, general purpose artificial technology can be at the forefront of innovation (Cockburn et al., 2018). As AI improves rapidly, its ramifications for production and our lives in general become more pronounced.

This discourse, outlined in brief, envisions AI at the heart of the future economy. Thus, a closer inspection of AI and its potential to reprise this general-purpose role is warranted. If AI can indeed achieve general application, it will change our economy and lives forever. In this regard, we must also consider whether we are prepared for this shock to the system and how it might be dealt with. As AI grows in influence, policy makers possibly should use this time wisely to appropriately modify their decisions on anything from education to employment and welfare.

Alongside AI, robotics is another, hotly-touted technology of our time. The world's stock of industrial robots, 550,000 in 1993, doubled to 995,000 by 2007. Research into the economic and employment consequences of this development began in 2013. Frey and Osborne (2013) calculate that 47 percent of jobs in the United States are at risk of replacement by robots and automation. Subsequent studies provide further empirical evidence of robots' impact on the economy, covering topics such as labour productivity, employment, and wages (Graetz and Michaels, 2015; Acemoglu and Restrepo, 2017). In particular, Acemoglu and Restrepo (2017), emphasise the threat of industrial robots pose to U.S. workers and their wages with empirical evidence. Broadly speaking, robots are expected not only to replace human workers but also to erode labour market conditions. This incites contemplation of how robots may affect both the lives of individual participants in a more volatile labour market and other economic sectors. The labour market, indeed, can be viewed as an indirect representation of the effect of robots on other interested areas, such as political economy and mental health. Falling incomes and the increasing risk of unemployment to workers may cause social unrest and affect the voting behavior of people. Similarly, the stress of a deteriorating labour market endangers the mental health of workers.

These assumptions entice an enquiry into the association between robots, political stability, and workers' mental health. If robot usage does undermine political stability, political leaders and policy makers possibly should strategies accordingly, acting to dispel social unrest and strengthen the political system. Equally, if robot usage aggravates the mental health of workers, policy makers and businesses may need to cooperate to mitigate this.

People's altitude of robots could also provides explanations of the mechanism between robots, voting behavior and mental health. Hudson (2019) examines the perception of citizens about the usage of robots and finds different altitude of robots in different socioeconomic groups. Older people tend to be more afraid of robots than young people. In terms of voting, different age groups have different preference on parties. Therefore, the use of robot may affect the voting outcomes, which has been discussed in chapter 3. In addition, older people afraid increasing use of robots and they are easy to die. Chapter 4 uses the mortality caused by drug and alcohol to measure the mental health of people.

1.2 Research Questions

1 **Can AI be viewed as a general-purpose technology ?**

The first research question of this study is whether AI can be viewed as a general-purpose technology, which will revolutionise an entire economy, or a normal one. A general-purpose technology stands out within long-term technological progress. The most important feature of a general-purpose technology is its widespread application, which reaches across industries and sectors. Rapid developments in AI and related technologies are drivers of economic activity and growth. AI can usually be divided into three categories: Robotics, Logistics Systems, and Learning Systems [1]. The sprawling development of AI and related applications is underlined by the variety of AI-related patents found at the U.S. patent office. An analysis of AI's representation across different areas will determine whether it means this key, general-purpose criterion. Evidence that AI is becoming a force in new industries as well as traditional ones, it could be regarded as general purpose in nature.

2 **How does changes in industrial robots usage affect voting outcomes in the United States ?**

The second research question of this thesis is how changes in industrial robot usage influence the American electorate. Given the lack of data on AI, we focus on the introduction of industrial robots to gauge the effect of technological change on the economy, especially the political economy. Whilst society is modernised by such sweeping technological progress, there is also political unrest. When new technologies replace older ones, they create new jobs but also make some workers redundant. Those affected may contribute to social tumult, challenging the stability of the political status-quo. The presidential and congressional elections are used as a measure of this political stability in the United States. Changes in industrial robotics, once again, indicate technological development. If industrial robotics sway election outcomes, this will speak to a larger relationship between technological change and political stability.

3 **What is the link between the use of industrial robots and the mental health of workers in the United States ?**

[1] Detailed classification of AI can be found in Table 2-1

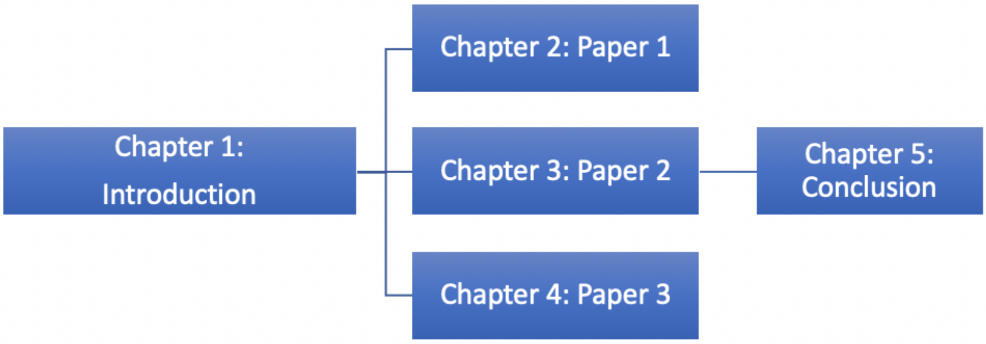
The third research question of this thesis is whether the usage of industrial robots can influence the mental health condition of workers in the United States. Whilst data on AI is inaccessible, information on industrial robotics allows us to examine the mental-health ramifications of technological change. The adoption of new innovations, such as robots, may lead to the redundancy of certain workers and their skillset, especially the least-qualified, as the job market demands different capabilities of their employees.
Such a scenario presents several concerns for workers: (1) Increasing fear of job loss to mechanisation; (2) Anxiety about lower future income; (3) Increased work-related stress and demand placed on the worker. Under these circumstances, "deaths of despair" will be more common, at the hands of drug or alcohol abuse, if not suicide. Simply put, we assume that social and economic deterioration leads to decline in workers' mental health and increasing mortality. Therefore, drug- and alcohol-induced fatalities amongst the working population are used as a barometer of mental health. Technological changes, to reiterate, are expressed by changes in industrial-robot usage.

To each of these research questions, a separate chapter is devoted. As a whole, this research surveys the economic effect of new technology, through the narrower lens of its impact on voting decisions and mental health. The study begins by using AI as representative of technological change, to ascertain whether AI is of general purpose to the whole economy. In the empirical studies which follow, industrial-robot data implies the impact of new technologies on voting outcomes and mental health, due to the unavailability of AI statistics.

1.3 Thesis structure

This PhD thesis is essay-based and comprises three papers in three separate chapters. Though each paper investigates a different research question, these are interconnected and address the same, overarching objective, which is to explore the relationship between new technologies and the economy. The structure of the remaining content of this thesis is illustrated in Figure 1-1.

Figure 1-1. Thesis Structure chart



Chapter 1: Introduction- Chapter 1 opens with the research area, original research objective, and thesis structure. It also explains the research questions, offering a brief contextual overview.

Chapter 2: Paper 1- This chapter presents the first paper, entitled "Artificial intelligence: the next general purpose technology". The purpose of this article is to determine whether AI can become the next general-purpose technology. It is discovered that the stock and growth rates of AI patents in logistics systems and deep learning is higher than robotics. In addition, AI applications become more popular in chemical and medical sectors than computer science peripherals, electronic applications, automotive applications by comparing the AI patent growth rate and average growth rate sector by sector. These findings indicate that AI origins from computer science, but developed more related to learning systems that can be applied broadly in other sectors. In other words, AI has the key characteristic of general-purpose technologies.

Chapter 3: Paper 2- Chapter 3 presents the second paper, entitled "Robots and election outcomes in the United States". This considers the effect of robot usage on the outcomes of presidential and congressional elections from 2000 to 2016 in the United States. The empirical research is conducted at the commuting zone level and robot usage in European countries is used as the instrumental variable of U.S. robot usage, circumventing the endogeneity problem. One of the main findings is the negative and significant effect of robot exposure on the weighted total votes of the Democratic Party in the U.S. presidential election, whereas there is a strong positive correlation between robot usage and the total Republican votes in the U.S.

congressional election.

Chapter 4: paper 3- Chapter 4 presents the third paper, entitled “Robots and mental health in the United States”. This section gauges the influence of industrial robotics on the mental health of U.S. workers, using drug-, alcohol-related fatality statistics, as well as all other factors, as an indicator of the latter. Ultimately, robot usage is found to be deleterious on the mental health of workers, reflected by a rise in the aforementioned kinds of death.

Chapter 5: Conclusion- This chapter concludes this thesis as a whole, presenting its main lessons, possible limitations, and directions for future research.

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Appendix 6B: Statement of Authorship

This declaration concerns the article entitled:	
Artificial intelligence: the next general-purpose technology	
Publication status (tick one)	**Draft manuscript** [x] **Submitted** [ ] **In review** [ ] **Accepted** [ ] **Published** [ ]
Publication details (reference)	
Copyright status (tick the appropriate statement)	I hold the copyright for this material [x] Copyright is retained by the publisher, but I have been given permission to replicate the material here [ ]
Candidate's contribution to the paper (provide details, and also indicate as a percentage)	The candidate contributed to / considerably contributed to / predominantly executed the… Formulation of ideas: - Considerably contributed to the formulation of ideas. (60%) Design of methodology: - Predominantly contributed to the design of methodology. (60%) Experimental work: - Predominantly contributed to the experimental work. (80%) Presentation of data in journal format: - Predominantly contributed to the presentation of data in journal format. (70%)
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.
Signed	Diling Xiang — **Date** 18/12/2020

Chapter 2

Artificial intelligence: the next general-purpose technology

Abstract

AI is a new, rapidly-advancing technology, which can imitate human behaviour and actions. This paper considers whether or not such technology is of general purpose and long-term import. The use of AI patents from the U.S. patent office, between 1990 and 2014, to inform this judgement is one of the ways it supplements previous scholarship. Indeed, this thesis contains a thorough review of existing literature on AI, including its role in research, innovation, and automation across the economy. The main findings of this research are as follows: 1. The stock and growth rates of AI patents in logistics systems and deep learning is higher than robotics; 2. AI applications are more popular in the chemical and medical sectors than in computer science, the electronic and automotive sectors by comparing the AI growth rate in these sectors and their average sector growth rate. These findings indicate that, though AI originates from computer science, it developed into something broader, reaching across various sectors. In short, it could be viewed as a general-purpose technology. Policy makers possibly should prepare for the reverberations AI applications will make as they become more widespread, with particular regard to education, healthcare, and the labour market.

Keywords: Artificial Intelligence, General Purpose Technology, Innovation, Patents.

2.1 Introduction

The recent strides made by AI suggest its suitability for general-purpose technology. Theoretical studies of it, which speculate AI's impact on employment, wages, and productivity, are numerous (Brynjolfsson et al., 2017; Acemoglu and Restrepo, 2018; Aghion et al., 2017). Aghion et al. (2017) deduce that AI is biased towards high-skilled jobs and against low-skilled ones. Acemoglu and Restrepo (2018) state the displacement effect of AI is stronger than other countervailing effects, thus AI increases output per worker and decrease the labour share of national income.

The growing theoretical attention paid to AI and its economic consequences is a testament to its importance. The biggest difference between AI and other new technologies is that AI has the potential to influence the process of innovation itself (Cockburn et al., 2018). There are three main technological aspects within the domain of AI - robotics, learning systems, and symbolic systems. Although AI originates within the field of computer science, advances in learning systems may broaden its range of applications. This paper seeks to ascertain whether or not there is, in this respect, enough evidence to declare AI can be served as a general-purpose technology, which is momentous in the long-term and widely appropriate.

Firstly, a comprehensive literature review is provided. Secondly, this paper empirically addresses whether or not AI is a general-purpose technology. AI development is reflected by data of associated patents from the U.S. Patent Office. The empirical research expands the study of (Cockburn et al., 2018). It still divides AI patents into the three, aforementioned categories. Chronologically evaluating AI patents, we discern differences across sectors and areas where normal patent activity is exceeded. If the related patents imply a growing trend towards learning systems or the expansion into new industries, the case that AI can be viewed as a general-purpose technology becomes convincing. This paper discovers that the stock and growth rate of AI patents in logistics and learning systems is higher than robotics. In addition, AI applications are more popular in the chemical and medical sectors than computer science, the electronic and automotive industries in recent years. Likewise, AI has made greater advances in deep learning than robotics. The application of AI also spans a broader range, from traditional to newer industries. These findings are consistent with (Cockburn et al., 2018), indicating that AI could be viewed as a general-purpose technology.

The remainder of the first paper is as follows: Section 2.2 introduces the literature on robotics, automation, and AI, both empirical and theoretical, focusing on their economic impact; Section 2.3 covers the literature of those who use patent data, which is the main data source of this paper; Section 2.4 explains some commonly used identification strategies of patent-data-related studies; Section 2.5 provides an explanation of the data, the research methodology, and descriptive analysis; Section 2.6 summarises the main findings of this paper and the plans for future investigation and the final section is conclusion.

2.2 Literature Review

AI and robotics technologies have become increasingly capable in recent times. For instance, The Electronic Frontier Foundation (EEF) has observed the swift improvement of AI in tasks such as voice-recognition and translation. AI can be defined as "a machine's ability to finish tasks by imitating intelligent humans" or "the capability of an agent to reach purposes in a variety of environments".

The likeness of AI to real humans has engendered fear that human labour could be completely replaced by it. Smith and Anderson possible fully replacement of human labour by AI. Smith and Anderson (2017) evidence this concern about AI and other new technologies in a large number of surveys, which exhibit the anxiety about AI's influence on the economy and labour. This compels us towards a fundamental economic question: to what extent will the replacement of human labour be and what will the ramifications be for productivity? Aghion et al. (2017) argue that AI may be positioned in the normal production of goods and services, replacing previously human capital and affecting economic growth and income share. However, the research frontier remains removed from a satisfying understanding of the effect of automation, AI, and robotics on productivity and the labour market (Acemoglu and Restrepo, 2018).

Recent publications and discussions of this issue usually fall into two categories. On the one hand, optimists argue that AI is no different from previous technological innovations, which increased labour demand and wages in the long-term. The advancement of AI offers benefits, such as in production. More immediately, AI can help deal with complex problems and has shorter computing time. It also facilitates technological learning and imitation between companies and industries, expanding knowledge externalities. Especially, AI promotes innovation, for instance, the creation of flying drones or self-driving vehicles.

On the other hand, pessimists see the advancement of AI as the death knell of human jobs and endeavour, especially given the number of industries in which it now spreads. Whilst AI was limited to computing activity in the past, its expansion to anything from voice recognition, psychotherapy, to even warfare suggests the loss of human advantage, if not man's superfluity, economic and otherwise. The extreme case would be Singularity, where the progress of AI will bridge the gap and become superintelligence (Nordhaus, 2015).

2.2.1 Literature of robots and automation

Research into the economic consequences of AI can be traced back to the study of robotics and automation. Robots can affect economic growth and employment by boosting productivity and automating routine works? Frey and Osborne (2013) initiate the discussion of automation and employment, assessing the risk to jobs. Taking an occupation-based approach, they sub-

mit that 47 percent of jobs in the United States are at risk of automation Frey and Osborne (2013). High-risk jobs, notably, still include several tasks that are difficult to automate.
This assumption that whole jobs will be automated, as opposed to individual tasks comprising them, could, in this respect, be misleading. For instance, Arntz et al. (2016) in their task-based evaluation, calculate just nine percent of jobs to be at risk, in a survey of 21 OECD countries. This deviates greatly from Osborne and Frey, downplaying the perceived threat of automation.
Moreover, the percentage of automatable jobs differs between countries; for example, the risk is 6 percent in Korea but 12 percent in Austria Arntz et al. (2016). Different states have different levels of technological development, worker education, and occupational distribution. Therefore, disparities in the impact of automation are to be expected. On this note, it is important to take the heterogeneity of countries and their jobs into account.
In any case, the estimated risk does not necessarily result in a corresponding loss of jobs. Obstacles in the implementation process are an obvious explanation for this. David (2015) grapples with this notion of a straightforward, positive correlation between automation and job losses. He contends that, as automation replaces human labour in one place, it simultaneously engenders work in another, necessitating other tasks complementary to the new process; equally, it increasing labour demand by boosting output. Jobs dealing with the machines themselves are rarely replaceable. According to the O-ring model of Kremer (1993), the value of remaining human labour will increase as automation improves the reliability of the production process. Professional commentators tend to overstate the substitution effect of automation, whilst largely ignoring the reciprocal relationship between automation and labour.
Whilst the critical discourse checks the hyperbolic pessimism which automation has often evoked, it still notes the reality of its threat, especially for low-skilled workers. As AI and robotics grow, so too the probability of job losses. A fall in employment figures is one thing but automation may also hinder the creation of new roles. In the past, new industries have recruited more workers than the number of deportees. However, this could soon change if these sectors can offer fewer jobs to labourers of intermediate skill or worse.
The future trend is towards increased production with less demand for labour. Wages are distributed more disproportionately to workers at the very top and very bottom of the scale, in terms of skill and income, whilst those in the middle miss out. Economists call this phenomenon "wage polarization", which may be caused by the substitution of middle-skilled jobs to automation. But machines cannot replace the middle-skilled worker entirely and retain their previous quality. There are, namely, two types of jobs for which automation is insufficient. "Abstract" jobs are the first of this kind, which require the worker to be persuasive, intuitive, creative, and solve problems. Second are "manual" jobs, which need situational adaption, the recognition of visual and aural signals. Such tasks are required of both low- and high-skilled occupations. In this manner, automation covers routine, usually middle-skilled

tasks, whilst the jobs at the top and bottom of the spectrum are somewhat shielded.

According to Goos and Manning (2003), this shift can be defined as "job polarization". It is commonly predicted that "polarization" will be a temporary circumstance, as middle-skilled labour will still be demanded by many jobs. David (2015) analyses data from the IPUMS between 1979 to 2012, plotting changes in the occupational employment share in the U.S. labour market. The share of four, middle-occupational jobs in the U.S. market drops from 60 percent in 1979 to 46 percent in 2012, supporting the existence of polarization. Furthermore, the time plots of mean wage by occupational skill in these same years evidence the link between employment and wage polarization.

Bowen and Mangum (1966) discern that technology makes jobs redundant but not work. In other words, irrespective of technology's role, the core determinant of employment is the demand for goods and services. The replacement of routine actions stems from the comparison of man and machine and their respective capabilities. At the same time, areas where humans have the upper hand, such as in problem-solving, adaption, and creativity, are also highlighted. Thus, replacing human labour with new technology is not without challenges and can even cause a shortage of these soft skills (David, 2015).

At this stage, there is not enough systematic research into the economic impact of robotics and automation. Though robot usage has increased dramatically since 1993, with the world total nearly doubling from 550,000 to 995,000 by 2007, the lack of critical evidence is a concern for economists. In comparison, the evidence for the economic effect of other new technologies, such as information and communication technologies (ICT) is plentiful (Basker, 2012; Bloom et al., 2012; Brynjolfsson and Hitt, 2000).

The slowdown in productivity growth in recent years has fuelled the desire to explore the impact of robotics. Graetz and Michaels (2015) systematically investigate the effect of industrial robots on several main economic variables, using a new dataset that includes a series of industries in 17 countries from 1993 to 2007. According to the definition of the International Federation of Robotics (IFR), the industrial robot is a machine that can be controlled automatically, reprogrammed, and is multi-purpose. Their analysis is based on a two-sector model, where one sector uses both labour and robots under constant elasticity of substitution and the other exclusively labour. They provide evidence of the positive effect of robot density on labour productivity and value added per worker, especially the decreasing marginal gains on productivity. According to the IFR's estimation, the current stock of industrial robots in operation is between 1.5 and 1.75 million; 39 percent of these are employed by the automotive industry, 19 percent by the electronics industry, 9 percent by the metal industry, and 9 percent by the plastic and chemicals industry. The varying prevalence of robots in the different sectors suggests the economic effect is industry-specific. By considering the specificity of country and economic branch, the OLS estimation is robust. Furthermore, the result is robust for the two-stage least squares (2SLS), which creates a replaceability index as a proxy of robot

density. Robot density, it is calculated, does not harm the employment when it is measured by aggregate working hours.
Graetz and Michaels (2015) detailed study is the first of its kind, providing a template for future research into the economic ramifications of robotics. Sharing their data source, Acemoglu and Restrepo (2017) nonetheless, apply a different empirical method to examine the effect of robots on employment and wages at an industry and country level. Notably, they formulate a cross-city design by using the data of commuting zones in the United States to investigate the exogenous factor of changes in robot explosion, which comes from the technology frontier. Based on this idea, the technological frontier is represented by trends in other developed economies and the local labour market by commuting zones. Acemoglu and Restrepo (2017) conclude that robot usage has a significantly negative effect on employment and wages. The robustness of these results is backed by the data. The IFR provides statistics of industrial robot usage in 50 countries (which account for 90 percent of total industrial robot usage) from 1993 to 2014. However, the industry-level data, also available from 1993, represents only 10 countries, or 41 percent of total industrial robot usage. The wage and employment figures are supplied by EUKLEMS and ESKLEMS. Thus, whilst Acemoglu and Restrepo (2017) comprehensively evaluate the impact robots have on labour-market equilibrium, their influence on employment and wages in other areas receives less attention. Having said that, the negative outcome implies the offsetting employment increase in other industries should be relatively small.

2.2.2 Literature of New Technologies and Labor Share

The previous, largely unmoving labour share is a cause for optimism. Kaldor (1961), in particular, offers several famous stylized facts of economic growth, which includes the constant labour share within a long-time period. Empirical evidence from the United States in nineteen centuries also supports this constancy (Acemoglu, 2008). Nevertheless, the rapid development of AI is eroding economists' confidence in the constant labour share. Advances in AI may offer short-term benefits to skilled labourers and holders of capital. However, labour will be immiserated over time, run based on the overlapping generation model (Sachs and Kotlikoff,2012).
Acemoglu and Restrepo (2016) generate a model for the effect of two opposing forces, the competition between which determines the change of labour share. On the negative side, the improvement of new technologies will replace tasks previously performed by human labour, decreasing labour share and real wages. On the positive side, technological development will create new jobs and provide more job opportunities for labour, restoring the labour demand. The interplay between these two forces could promote balanced growth if certain conditions are met. In response to this model, Autor and Salomons (2018) analyze a series of channels

that automation affects labour share based on the model generated by Acemoglu and Restrepo (2016). Critically, decreasing employment, working hours, and wages do not only reflect labour replacement, but also the relative increase of wage bill (products of one hour divided by wages for one hour) and value added (Autor and Salomons, 2018). In other words, if the increase in growth rate of wage bill is slower than the rate of value added, it suggests that jobs are being lost to automation. The pair find that automation does not replace labour but results in the decrease of value-added labour share. It is likewise observed that the boost of labour replacement on productivity growth, which vanished from the 1970s, has returned since the 2000s. Another model, devised by Susskind et al. (2017) even predicts the ultimate replacement of labour. The consequences of automation vary from one model or theory to the next .

Turning to the empirical side, an increasing number of scholars investigate whether the improvement of new technologies diminishes labour demand or wage growth. Common ground is the fact that the share of labour in national income decreases in many countries, perceptible in the 1990s and undeniable since the 2000s (Elsby et al., 2013; Karabarbounis and Neiman, 2013; Piketty, 2014). Alexopoulos and Cohen (2016) highlight that technological progress increased productivity and decreased unemployment between 1900 and 1949 in the United States. Nonetheless, the development of routine-replacing technologies reduces employment, as in the case of European, middle-skilled labour (Gregory et al., 2016).This negative effect on employment, indeed, is greater than the offsetting demand spillover effect.

The growing use of industrial robots increases labour productivity and wage levels; robot incorporation exerts no discernable impact on aggregate working hours and leads to a modest employment increase amongst high-skilled labourers, according to data from 17 European Union countries (Graetz and Michaels, 2015). In addition, Jager et al. (2015) surveying 3,000 European manufacturers, find that robot usage has no direct impact on employment, though there is a positive correlation between robot usage and labour productivity. Mann and Puttmann(2017) distinguish between the manufacturing industry, within which automation drives down employment, and the service industry, within which employment is swelled by it; the net impact on employment is positive by using the patent data. Though the penetration of industrial robots, in the years 1990 to 2007, results in a fall in employment and wages in the United States (Acemoglu and Restrepo, 2017), the fact this conclusion is drawn with limited, cross-sectoral scope, there is a focus on heavy industry, for instance, might offer a note of caution to those intending to generalise this finding. In the future, robotics will be more widely applied, including in service-provision, eliciting different reactions from the labour market than in the present-day.

In summary, the overriding critical impression is that new technology, whether slowly or not, surely reduces employment. Notably, a common characteristic of research in this field is to cover one specific invention, such as robots to proxy the automation or technological improvement. Uniquely, Autor et al. (2017) assess the relationship between overall productivity growth and employment by using the data of 19 countries across 35 years, at both country and industry level. They deduce that employment decreases when productivity increases at the industry level. However, the opposite is true at the country level, as employment rises with productivity . Since the latter effect is more widespread, it can be said that augmented productivity encourages employment. Whilst there is a shift in the skills required, aggregate labour demand goes up.

2.2.3 Literature of AI

Within the backdrop of long-term examinations of economic automation, the critical spotlight has become fixed on AI, with the sense of its fixed identity and its wide range of applications. The effect of AI on employment and productivity growth is still the main study interest. Nonetheless, research has also branched out to topics such as the innovation process.

As there exists many new transformative technological innovations could largely improve productivity growth, the observed productivity shows a lower growth in the meantime. Discussions of this contradiction fall into two categories: either an optimistic stance towards technology is adopted or disappointment is expressed through analysis. Brynjolfsson et al. (2017) state that these two type of arguments can exist in the same time as the economy is experiencing a restructuring period due to the transformative technology. The main source of optimism is the great strides in AI, particularly machine learning. The pessimism mainly stems from the slowing rate of productivity growth in many advanced countries since the middle of the 2000s. It should be noted that the possibility of the recession having lessened productivity has been excluded.

Brynjolfsson et al. (2017) provide four possible explanations for the paradox of technological improvement and the slowing rate of productivity growth. The first gainsays optimism, as the improvements transformative technology may offer to certain industries are relatively small. The second underlines the possible error made when measuring productivity, namely the failure to acknowledge prior productivity growth caused by technological advancement. Despite this, Cardarelli and Lusinyan (2015); Byrne et al. (2016); Nakamura and Soloveichik (2015); and Syverson (2017), utilising different data and approaches, all exhibit that mismeasurement is not the main reason for decreasing productivity growth.

The third explanation relates to the distribution and attainability of new-technology benefits. Technological gains advantage a limited proportion of the economy; furthermore, these beneficiaries often block others from accessing the innovation. Andrews et al. (2016) note a growing profit and productivity disparity between frontier companies and those at the bottom, lending credence to this claim. In the last explanation, optimism and pessimism co-exist, given that new technologies cannot become fully realised overnight, especially when they are general-

purpose in nature. The benefit from a general-purpose technology on productivity growth requires a sufficient stock of capital, the accumulation of which also takes time. In summary, it is more difficult to acquire short-term gains from AI, which, after it has been accepted into organisations, necessitates the arrangement of complements and other such restructuring, than from other forms of automation.
In order to show the unsuitability of using historical productivity growth to project future performance, Brynjolfsson et al. (2017) regress the past ten years' productivity growth with the next ten years' labour, total factor and utilization-adjusted productivity growth in the U.S. market since 1948 to 2016.

Aghion et al. (2017) continue the study of the relationship between AI and economic growth. Firstly, AI is introduced into the process of producing goods and services, where labour, in a rising variety of tasks, is replaced by capital. Based on the economic automation model of Zeira (1998), automation boosts growth in the long-run. However, this theoretical positive relationship contradicts with the Kaldor (1961) facts, which states the stability of growth rate. The empirical evidence of the U.S. economy in the 1990's also supports the stability. Acemoglu and Restrepo (2016) propose a resolution, by assuming the new-job invention rate to be equal to that of old-job replacement. Therefore, the share of automated tasks is constant, along with a constant capital share and growth rate.
Aghion et al. (2017) add the cost disease theory of Baumol (1967) into the model of Zeira (1998), projecting different scenarios, including balanced growth with a stable capital share under almost total automation. Balanced growth can be achieved by a gradual rise in the share of automation in the economy, though the fraction of GDP related to the automated manufacturing and agricultural industries actually decreases, as Baumol's cost disease explains. Aghion et al. (2017) investigate the effect of AI on the internal structure of enterprises, with reference to skill and wage distribution. They observe that AI affects the fraction of low- and high-skilled labourers across the whole economy. In addition, firms using more AI applications may outsource low-occupation tasks to other enterprises and provide higher wages to those low-skilled workers inside the company. Moreover, if AI is introduced into production technologies for new innovations, it will leads to potential increases of growth. Whether this growth increase is temporary or permanent depends on whether AI is exogenous or endogenous. Endogenous AI may eliminate the importance of population growth on economic growth as AI workers are better at generating new ideas than people. Ergo, endogenous AI is an important topic for future research. Finally, Aghion et al. (2017) discuss whether AI could theoretically produce singularity, attaining a mix of both positive and negative results.

Turning to the effect of AI on employment and wages, Acemoglu and Restrepo (2018) with their task-based model, submit that AI will affect labour demand in two opposite directions.

From a negative perspective, the development of AI has a displacement effect, as human labour is replaced by AI and machines for an increasing number of tasks. The reason we speak of tasks is simple; automation and AI can rarely perform the canonical production function. As the classical production function can be expressed as F(AL, BK), technological improvement can be regarded as an augmentation of production factors (labour and capital). However, the substitution effect exists in many tasks that can be completed with the corporation of labour and machines, such as textile production. Therefore a task-based approach is most appropriate, as some tasks can be generated by either labour or capital. The comparative advantage between labour and capital suggests the productivity of labour should be different for different tasks. In this task-based framework, automation and AI are conceptualized as the increasing number of tasks that can be performed by capital. Capital will substitute labour in the production of these tasks if the cost of using capital is sufficiently low, leading to worker displacement in those automated tasks. Subsequently, labour demand and so too wages fall. The reality, which is that technological development can improve productivity but drive down wages, is often overlooked. When the labour demand is elastic, the decrease in labour demand results in rising unemployment. Diverging from the classical view of factor-augmenting technological advances, this task-based method re-depicts productivity-augmenting technologies as simultaneously decreasing employment and wage rate.

On a positive note, there are other forces at play that serve to balance labour demand. The first one is the productivity effect of cost-reduction caused by automation, which leads to greater labour demand for non-automated tasks (David, 2015). Due to automation's savings, the price of goods and services in those sectors also drops. Resultingly, the purchasing power of households, in relative terms, is higher, increasing demand for goods and services.

Then, there is capital accumulation; due to automation, many production processes become capital-intensive. The demand for capital experience significantly grows, triggering capital accumulation and succeeding increases in labour demand. The third factor is the deepening of automation when technological progress raises the productivity of capital for those automated tasks. As these tasks have already been automated, no further displacement effect will occur. However, this elevated productivity still brings its positive results, raising the demand for labour.

Notwithstanding these, Acemoglu and Restrepo (2018) emphasize that the total positive effect of these first-order forces is not enough to offset the negative effect of displacement on labour demand. On this note, the final and the strongest force is the creation of new tasks. The growth of automation and AI will engender new tasks, industries, and working positions. AI can be applied in many branches, not only in manufacturing but also in services, such as education and healthcare. The generation of new roles is a reinstatement effect, augmenting labour demand. A balance between displacement and reinstatement is how balanced, technologically-driven growth and improvement are envisioned.

Aside from the economic repercussions of AI, how it affects the innovation process has also become a matter of critical concern. As discussed previously, AI could improve the efficiency of producing goods and services. And yet, more importantly, AIe may fundamentally alter research and development, as hitherto practiced, in its role as a general purpose technology. Cockburn et al. (2018), selecting patent data from the United States Patent Office (Marco et al., 2015) related to AI, contend that AI can indeed change approaches to invention and innovation by serving as a general-purpose technology.

2.3 Literature of Patents

Due to the lack of empirical studies on the effect of AI, this paper tries to find some empirical evidence to support the theoretical hypothesis. AI has emerged as one of the most rapidly developing new technologies in recent years. How to measure technological change is a matter on which economists have long-since pondered. Of the many suggestions, each method presents its benefits and drawbacks, with critical consensus yet to be reached on any one approach. The majority of these are indirect estimations, or rather only a particular aspect of the process in question is reflected by the indicator.

2.3.1 Development of Patents

Even so, patent statistics are a popular yardstick. Patent works as a policy tool, incentivizing invention and innovation by guaranteeing the protection and exclusiveness of the invention. Scotchmer (2004) states that the patent system strengthens the inventive activities in various methods. Usually, the disclosure of new knowledge is through the revelation of invention, when the information is protected rather than diffused, encouraging the creation of new inventions by others. Patents have played a more comprehensive role in the economy since significant market and policy improvements in the 1980s (Zuniga et al., 2009). Due to the ever-stronger competition between different countries, the rapid development of information technologies, and the increasing significance of RD-intensive enterprises and start-ups, patents have become more and more widespread. The more competitive the market, the more pivotal the protection of intellectual property rights and thus the firm's economic value. As mentioned, the tailoring of legislature to the advantage of patent owners began in the 1980s. The establishment of the Court of Appeals of the Federal Circuit (CAFC) in the United States was one such key moment, so too that of the European Patent Office. Japan also adjusted its laws in the 1990s to help patent owners protect their inventions. Thanks to these efforts, the stock of patent applications around the world experiences boomed during the mid-1990s until the mid-2000s and continues to rise even today. According to USPTO statistics, the number of patent applications, on average, grew 7 percent annually between 1995 and 2005.

2.3.2 Patent Data and Technological Development

Patents are possibly the most commonly used indicators of technological output, based on the assumption that the number of inventions is positively correlated with the number of patents. Patent data can measure the inventive performance of different countries, states, companies, and individuals. The literature which utilized it can be divided into three groups. The first of these predominantly focus on the effect of technological change on economic performance. For individual inventors, Keller and Holland (1982) find a significant (positive) correlation between the number of inventor patents and their rating of superior performance. At the firm level, Hagedoorn and Cloodt (2003) evidence that the number of patents assigned to a firm indicates its technological development. Similarly, de Rassefosse and de la Potterie (2008) demonstrate that the number of patents, on a country level, is highly correlated with the extent of R&D activity.

The second purpose of patent data measures technological diffusion between different countries. A concept called the technological balance of payment is used for this. Information about patent flows from one country to another is implemented to calculate the technological balance of payment. In addition, patent indicators track the globalization of a particular innovation by analyzing the address of inventors. The final direction of research is related to the innovation process, especially scrutinising the achievement of R&D activity. Studies in this direction usually evaluate the association between innovative input, patent, and productivity. Though patents are widely accepted as inventive activities, they cannot indicate all of an invention's research inputs. Moreover, an invention is not required to be implemented after being patented. Some surveys suggest a good deal of patents never come to fruition as their economic reward is insufficient. Pavitt (1988) puts the proportion of unrealised patents ,either industrially or commercially, at up to 40 percent: 18.7 percent of patent holders abandon the pursuit of their patent to keep it secret and prevent competitors from devising similar inventions, whilst 17.4 percent are simply never used.

A major indicator of innovative activity, patent data has advantages and disadvantages. In terms of the former, patent data includes various types of technologies, especially emerging ones, on which it is difficult to find another data source. Patent data includes comprehensive information on the invention process: the full title and explanation of the patent, the corresponding technological area, name and address of assignee, assignor and applicant, citations and reference, to name but a few details. Moreover, patent data is readily accessible to researchers and there are a huge number of new patent applications every year all over the world. This is in contrast to a lot of survey data, to which public access is limited for privacy reasons. Usually, patent data can be downloaded from different patent offices, regional or national, and the data has already been formatted. Patent data also has the unique advantage of covering both geography and time. A patent system includes information from all countries in different years and can be used directly in electronic format. For example, the first patent framework contains the data for nearly all OECD countries since the 1990s. Finally, patent data is closely linked to innovative and inventive activity, for almost all inventions and outcomes for business purposes are patented.

Nevertheless, patent data has several drawbacks. For example, not all inventions qualify to be patented. This information, thus, is missing from patent data, to which Pavitt (1988) draws attention. Most of these inventions contribute to non-technological sectors, such as the arts, and the inventor may choose to protect their creation in other ways. Secondly, the propensity to patent varies between different sectors and industries. For example, in order to deter the entrance of new competitors to the market and to maximise the benefits, a patented invention in electronic sector is always accompanied by other patent applications which make subtle adaptions to the original invention. This phenomenon, known as patent flooding, means the number of patents in the electronics sector is much higher than in other branches. Similarly, patents vary between firms. It is easier for large companies to cover the cost of patented inventions than small and medium-sized ones, as big enterprises can apply the patents to large productions. In addition, Griliches et al. (1986) note the highly skewed distribution of patent value; almost all patents are virtually worthless, with only one percent valued at more than \$70,000 (France) and \$120,000 (Germany), based on the empirical evidence. In other words, the majority of patents are not applied industrially and have negligible value, with only a few exceptions. Therefore, the number of patents alone may be a misleading indicator, due to the heterogeneity between different patents. This skewed value-distribution is not a unique drawback of patents, but a common problem of innovative activity. Moreover, the legal framework and rules of each patent office depends on the country. Consequently, it is not appropriate to compare patent data between patent offices and, thus, better to use patent statistics from the same patent office for comparative analysis. Time-series investigations should take historical changes in patent-related regulations and rules into account. Though patent statistics are not a wholly accurate representation of innovation, strategies can be employed to minimise the bias. For instance, weighting the data or narrowing the focus to industry-level analysis could address the issue of varying tendency to patent in different industries.

2.3.3 Criteria of Using Patents

Knowing its advantages and disadvantages, it is necessary to introduce criteria for compiling patent data. Whether the patent data permits meaningful interpretation depends on the appropriate choice of methodology for gathering the statistics. The basic rule for this is to consider the relationship between the chosen criteria and the research question. For instance, if the goal is to assess the innovative performance of different countries, the indicator should be based on the residence of the inventor. However, if the purpose of the study is to investigate the invention's ownership, it would be better to take the residence of the applicant.

Certainly, reference date and country of attribution are two main criteria when compiling indicative patent data. Generally, it is inadvisable to compare indicators from different patent offices, due to differences in patent laws and frameworks. For instance, the patent counts from the United States Patent Office cannot be compared with those from the European Patent Office. In terms of the reference date, a patent file usually contains a series of dates, such as priority date, application date, and grant date. Only one of these can be chosen as the reference date to reflect the attributed year of patents. The priority date, as the earliest in the patent application process, is the closest to the day of invention. The application date is the day when the patent application is submitted to the patent office. A patent application is first filed in the domestic office, before it is transferred to other countries. It is usually around 12 months after the priority date when this process is completed. Finally, the publication date records the disclosure date of patents to the public (usually 18 months after the priority date) and the grant date the time when the patent rights are authorized to the applicant (on average, some 3 or 5 years after the priority date). If the aim is to gauge the performance of inventions, using application or grant date results in a series of biases, due to the delay. Furthermore, the delay between application/grant date and priority date varies across countries, precluding comparison of patent data across different countries. Priority date, however, is not affected by legal or administrative practice, nor inventor strategies.

As such, it is the most appropriate date to use when compiling patent data to reflect inventive activity. In respect of reference country, there are again several options, such as the country of inventors, applicants, and priority office. The applicant country denotes the firm which owns the patent, demonstrating the inventiveness of firms from that country, but not necessarily the location of inventive facilities. In contrast, the inventor country reflects the inventive performance of a particular country's laboratories. The priority country suggests the attractive power of a given country, in terms of the quality and cost of protecting inventions at a given patent office. The inventor's country of residence is recommended when amassing patent data to measure inventive performance, whilst applicant address is a more appropriate reflection of the marketing strategy of firms.

Broadly speaking, an economic interpretation of patent data relies on its systematic classification, for instance, into technological fields, industries or sectors, regions and institutions. In other words, by connecting patent data with other information, such as company name, country, and industry code, it is easier to obtain economic and social insight. The technological field is one of the most common classifications of patents, as most of them pertain to inventions of techniques and naturally reflect the technical variations. In particular, this approach matches is relevant to inventions of emerging technologies, for which alternative data sources, outside of patent data, are lacking. Since patent data offers broad and chronological coverage, it offers understanding of technological trends, advances, and impacts.

To make searching for them more convenient, patent offices assign codes to each patent. The International Patent Classification (IPC) system has become a commonly accepted method of classification around the world. The IPC system divides patents into technical fields according to their function or application. There are eight main sections, such as human necessities, physics, and electricity, as well as 20 subsections. The United States Patent Office, on the other hand, has its own USPC classification. This shows a hierarchical order when generating sub-classes from the main ones, thus providing more detail than the IPC system. Likewise, the Japan patent office has its own extension of the IPC, the file index (FI) classification. The process of sorting patents into corresponding technical fields can be achieved by the following methods: keyword searching a particular technical field in the list of classes; keyword searching a given technical field in the description of patents; using a combination of these two.

Patent data, as mentioned, also allows analysis at the industry level by identifying those branches linked with those technologies they protect. In this way, patent data and industry-level data can be matched, providing a useful tools for evaluating significant policy making studies: patent data is a measure of the inventive performance of industries, as an indicator of R&D output in the knowledge production function (Ulku, 2007); it also implies how countries specialize in industries, as well as the effect on trades and productions checking the dissemination of technologies across industries.

As far as allocation of patent to industry is concerned, there are two options: either it is attributed to the sector of the inventing firm or that in which its technology finds its application. Moreover, patent data allows the regional specialization of innovative activity to be identified, whereby policy makers can compare inventive performance by area . Assigning patents to their corresponding institutions is another useful classification of patents data. These institutions can be individuals, private enterprises, universities, or public organizations, depending on the legal status of the patent owner. Private companies usually include a suffix, such as “INC”, “ING”, or “LTD”, in their titles. Van Looy et al. (2006) even develop a means of identifying patent institutions via this logic. Finally, patent data can be also classified by the company holding the patent and inventor of the patent. These various categories of patent data facilitate a more fruitful analysis of policy and economic issues.

2.4 Identification

In econometrics, consistency is a required property of an estimator and identification is a necessary condition to decide whether an estimator is consistent. Therefore, the process of identification is crucial to the empirical estimation. It ensures that the estimate of a structural parameter is an estimate of that parameter and not an estimate of other factors. This section summarizes several identification strategies from studies which utilise patent data.

The first of these is the first-differenced generalized methods of moment (GMM) approach, which is one of the most commonly used, especially for dealing with endogeneity between dependent variables. Ulku (2007) investigates the relationship between R&D activity, innovation, and economic growth by estimating the innovation function from the endogenous growth model. Innovation is the explained variable and is represented by the patent flow. In terms of explanatory variables, knowledge stock is reflected by patent stock and R&D intensity by its expenditure. The identification technique used in this paper is the GMM system of Arellano and Bover (1995). This GMM estimator can also be used for the issue of patents and market value. Blundell et al. (1999) applying patents as the dependent variable, observe that market share has a strong, positive effect on patents, based on UK evidence between 1972 and 1982 at the first stage. Prior to this study, scholarship of market value and innovation had mainly considered US data, of either R&D or patents. Afterwards, the market value in levels is taken as the dependent variable and all of the firm variables on the right-hand side are instrumented by their lagged value. The main findings are the significant effect of patent stock on market value and the significant and positive coefficient of the interaction term of patents and market share, supporting the argument that patent stock produces higher returns for those firms with higher market share.

The second strategy is three-stage least squares (3SLS) estimation, which combines multivariate regression with two-stage least squares. This method commonly tackles R&D spillover issues. Jaffe (1986) is one such pioneer, examining the impact of technological opportunity and R&D spillovers on the manufacturing R&D department's productivity. The latter is ascertained by the patent applications of firms, the accounting rate of return, and market value of the firm. Each measure has its own regression model. For example, when using the rate of return (defined as the difference between gross operating income and capital stock) as the dependent variable, the independent variables includes the market share, the stock of accumulated R&D investment, and a series of industry dummies. However, the R&D stock, its market share, and capital stock are endogenous. Jaffe (1986) utilize the industry R&D as the instrument of firm's market share, industry minimum efficient scale (MES) as the instrument of firm's capital stock, and the spillover pool for the R&D stock. The spillover pool is a weighted sum of other firms' R&D; the weight is calculated by the proximity of the firm's technological position, which is, in turn, determined by the distribution of the firm's patents across different patent classes. Measuring per dollar, a firm's R&D creates more patents when surrounded by neighbouring firms that are themselves highly active in this area.

Mohnen and Lepine (1991) apply the spillover pool theory in their industry-level investigation into the influence of R&D and foreign technology payments on the technological knowledge of Canadian firms. A variable cost function reflects technological knowledge, where independent variables include labour, materials, and foreign technology payments; variable inputs, physical capital, and R&D stocks are quasi-fixed inputs and outside R&D pools are an exogenous variable that proxies technological change. The exogenous outside R&D pool is constructed by using the patent flow matrix of patents granted across different sectors in Canada in the year 1978. The matrix is computed by the proportion of own-sector patents that being used by other sectors. This research also uses 3SLS estimation, where capital and R&D stock are instrumented by their one year lagged value. Mohnen and Lepine (1991) ultimately detect a complementary relationship between own R&D stock and foreign technology payments, as well as a substitutional relationship between own R&D and R&D spillovers.

The third strategy tests the causal relationship between the dependent and independent variables, but usually for time-series data. Diebolt et al. (2018) examine the effect of innovation on economic growth, evidencing its contribution to growth, though only in France, the United States, and the United Kingdom, and only in certain time periods. This is obtained by testing the direction of causality between patents and GDP per capital through the augmented VAR model.

Treatment group analysis is the fourth approach. Moser (2005) posits that patent laws affect the distribution of innovation across sectors by comparing the treatment group (without patent laws) with other countries.

The fifth adopts the nonlinear least square estimation, especially for the research into the link between the private and scientific value of innovation. Patent citations have been discussed as a good proxy of innovation. Hall et al. (2005) regress Tobin's q to the ratio of R&D to physical assets, patents to R&D, and Citations to patents, surveying U.S. patent and citation data from 1963 to 1995 and combining this with compustat firm data from the manufacturing sector between 1976 and 1995. The regression also includes time dummies and the industry fixed effect. They determine a strong, positive correlation between patent citation and market value of firms; market value increases by 3 percent for one more additional citation per patent. In principle, the endogenous independent variables would necessitate a differenced estimator, but this would cause significant downward bias in the case of a slowly-changing independent variable, such as this study has (Griliches et al., 1986).

Finally, after relaxing the restriction of equal mean and variance, possion distribution and a negative binominal model can be employed. Bound et al. (1982) discern a significant relationship between patenting and RD. Per dollar, the R&D of small firms produces more patents than at large firms, based on figures from the US from 1972 to 1978. Meliciani (2000) also explores the impact of R&D expenditures on patents by using the panel data of 12 OECD countries from 1973 to 1993 and a negative binominal model.

2.5 Documentation of Data

2.5.1 Background of AI

Nilsson (2009) defines AI as an approach to make machines become intelligent, which means machines have the ability to function appropriately and have foresight in their environments. Observing the evolution and history of AI, it can be categorized into three correlated but separated parts, which are symbolic systems, learning systems, and robotics respectively. The study of AI can be traced back to the 1960s and most related researches focuses on symbolic systems. Newell et al. (1958) state the premise of their “symbol processing hypothesis” is to imitate logical human decision-making by using processing symbols. Though symbolic systems may experience significant breakthroughs in future, this approach will not be a key aspect of AI applications, nor at the core of recent progresses of AI that are more related to the stream of machine learning.

The second milestone for AI is the emergence of robotics. Robots, machines which can carry out human work, were introduced in the 1940s and have become very popular since the 1980s. Industrial robots account for the most important AI applications of today. And yet, they can only perform specific tasks in a controlled and confined environment, not possessing some of the more advanced AI features. Consequently, the invention of more reactive robots, which can confront given types of simulated situations, is an improvement in this field. Brooks (1990) is one of key drivers of this development, pioneering the assignment of feedback mechanisms that help to achieve practical and responsive robots for given applications, rather than the those that imitate human intelligence.

Learning systems, which have become the core content of AI, is the broad label which can be attached to the final area. The aim of these is to generate a reliable and precise mechanism to predict certain events based on given inputs. Furthermore, a particularly important concept in the learning system is the neural network, which is a program that can produce outputs by converting a series of inputs. This process, considering both weights and thresholds and adjusting weights to decrease the chance of error, selects the most realistic outcome. In this respect, as Rosenblatt (1958) points out, neural networks have the ability to learn, as it is imported more inputs. From the 1980s until even the mid-2000s, the storage capacity of neural networks was one of the biggest obstacles to ensuring accurate prediction in the face of huge data sets. Since then, several new algorithmic methods, which employ multi-layer networks, have arisen, allowing powerful and accurate prediction amidst a mass of data. Based on these technical advances, the practical performance of research projects has greatly improved since

2009, which, for the large part, can be attributed to "deep learning" (Krizhevsky et al., 2012).

2.5.2 Methodology and Descriptive Analysis

This paper takes the work of Cockburn et al. (2018) as an example, expanding their research by using patent data related to AI to proxy the development of AI. First of all, this research decides to work on the historical masterfile of the United States Patent Office from Marco et al. (2015). This historical masterfile includes the information of patent numbers, USPC class, USPC sub class, NBER category, and application date. The reason for selecting this data file is that the USPC classification offers individual categories for AI and robotics, classes 706 and 901 respectively. According to the USPTO definition, class 706 is a class for artificial intelligence type computers and digital data processing systems and products for emulation of intelligence; and containing systems for reasoning, machine learning and neural networks. There are several subclasses to class 706, such as knowledge processing systems, machine learning, and neural networks. Therefore, it is convenient to divide patents related to AI into the symbolic systems, learning systems, and robotics by using the USPC classifications. This paper selects patent data with USPC classification numbers 706 and 901 from the historical masterfile. Thereafter, it retains patents between 1990 and 2014, sorting by application date to collect a sample of 16,088 observations. According to the USPC subclass, this paper further allocates these patents to corresponding AI areas, such as symbol systems, learning systems, and robotics.

It should be noted that some AI patents are not included in either class 706 or class 901. As a second step, this study examines another data file called documentid, which contains patent number, application date, and invention title. Considering the requirements of future analysis on person who applies for the patent. This paper merges a USPTO dataset called assignee, which includes assignee name, address, and country, with the documentid dataset. By searching keywords related to the three main AI streams for the invention title, the sample of AI patents can be expanded, mimicking Cockburn, Henderson and Stern (2018). If the invention title contains any of the three main AI area keywords, this patent relates to AI. Detailed information on keyword allocation is provided in Table2-1. The upshot is an additional 22,738 AI patents.

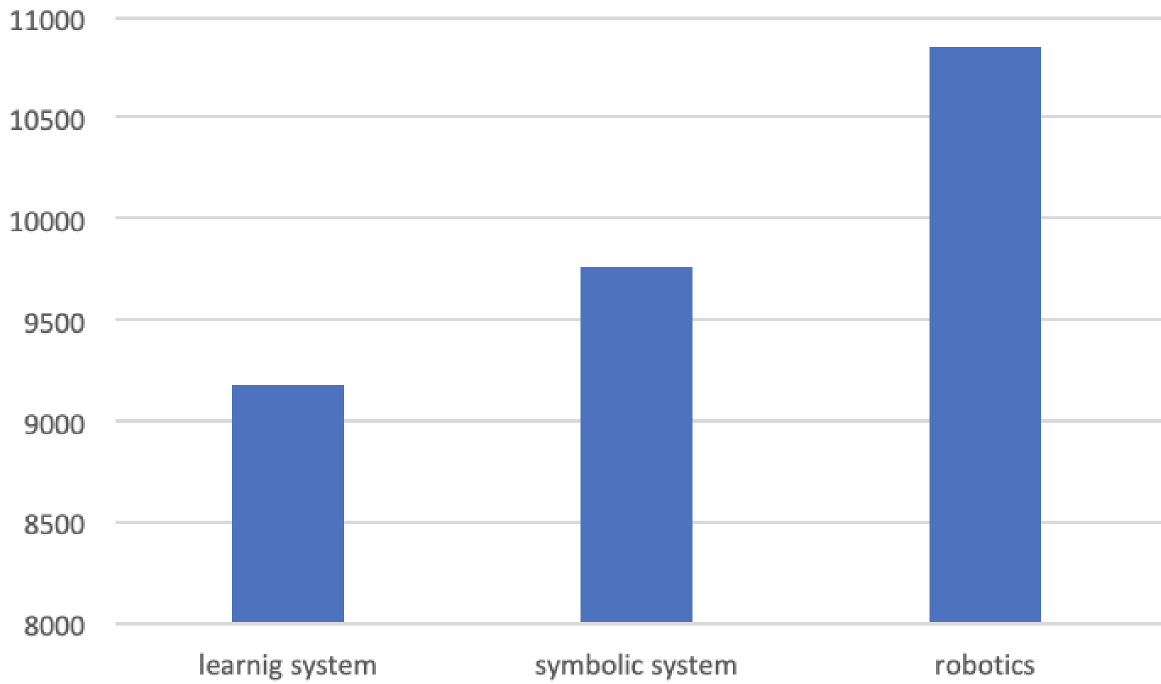
The next step is to divide these patents into their corresponding AI streams by relating the search words with one of the streams. For example, if the invention title contains "natural language processing", it is a symbol systems AI patent. To reiterate, pre-1990 and post-2014 patents are not considered. To avoid patent duplicates, the historical masterfile and documentid files are merged by patent number. Matched observations, those with the same patent number, can be filtered out. This unique and streamlined data file comprises of 29,767 observations and other summary statistics are displayed in Table2-2. Thus, though using the same original data and approach, this paper obtains more observations than **?**, who source only 13,615 patents.

Table 2-1. Key Words Summary

Symbols	Learning	Robotics
natural language processing	machine learning	computer vision
image grammars	neural networks	robot
pattern recognition	reinforcement learning	robots
image matching	logic theorist	robot systems
symbolic reasoning	bayesian belief networks	robotics
symbolic error analysis	unsupervised learning	robotic
pattern analysis	deep learning	collaborative systems
symbol processing	knowledge representation and reasoning	humanoid robotics
physical symbol system	crowdsourcing and human computation	sensor network
natural languages	neuromorphic computing	sensor networks
pattern analysis	decision making	sensor data fusion
image alignment	machine intelligence	systems and control theory
optimal search	neural network	layered control systems
symbolic reasoning		
symbolic error analysis		

Based on the merged file, this paper ascertains the frequency of symbolic systems, learning systems, and robotics. Table2-2 depicts these three, evenly distributed groups: 9,171 learning patents (30.8 percent), 9,754 symbolic system patents (32.8 percent) and 10,331 robotics patents (34.7 percent). The unclassified observations are identified as AI in general. This distribution resembles the result of Cockburn et al. (2018).

Table 2-2. Summary Statistics



This paper also generates the time graph of patent distribution in different areas in Figure2-1. This figure shows that patents of both symbolic and learning systems tend to increase, though several negative shocks are detected within the period. The highest increase in learning systems patents (847) occurs in 2013 and in symbolic systems patents (961) in 2014. The highest rise (830) in robotics patents is in 2010, before a sudden slump and steady decrease. The possible explanation of the fall in 2010 could be the mature development and application of robotics. Inventors may put more attention on new technologies, rather than mature technologies, thus the patent number of robotics falls after 2010. To assess the level change, this paper investigates the growth rate of patent stocks in three areas, the detailed statistics for which Figure2-2 displays. All three rates of growth lean towards decline, before stabilising after 1999. Learning and symbolic systems maintain a higher growth rate, close to 10 percent, than that of robotics, which is (around) 4 percent. This reveals that the recent focus in AI development has been on learning systems and symbolic systems more than robotics.

Figure 2-1. Patent flows of learning systems, symbolic systems and robotics

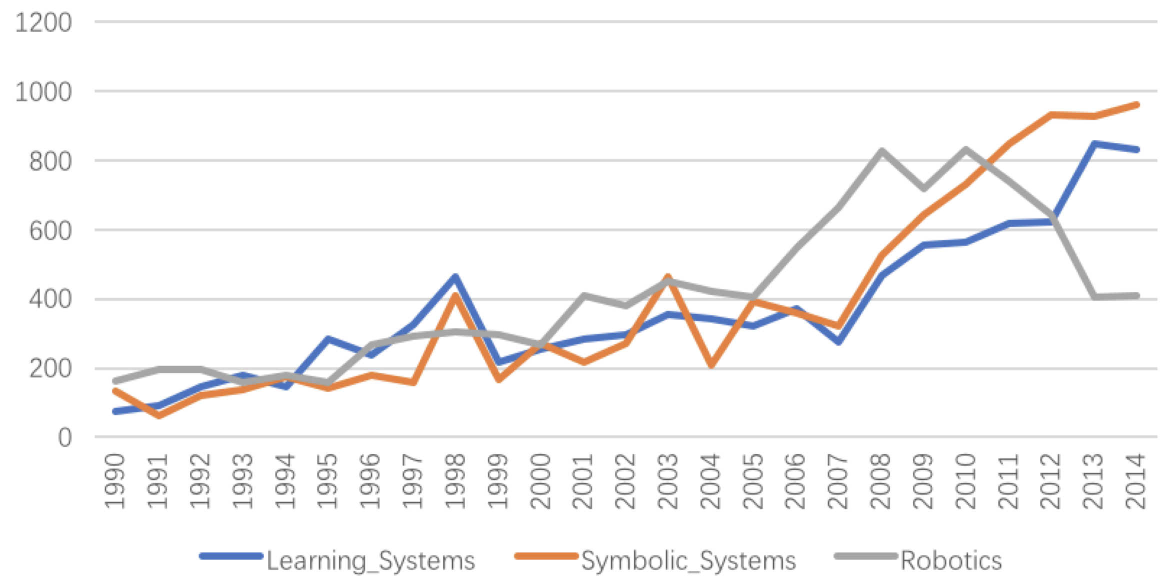
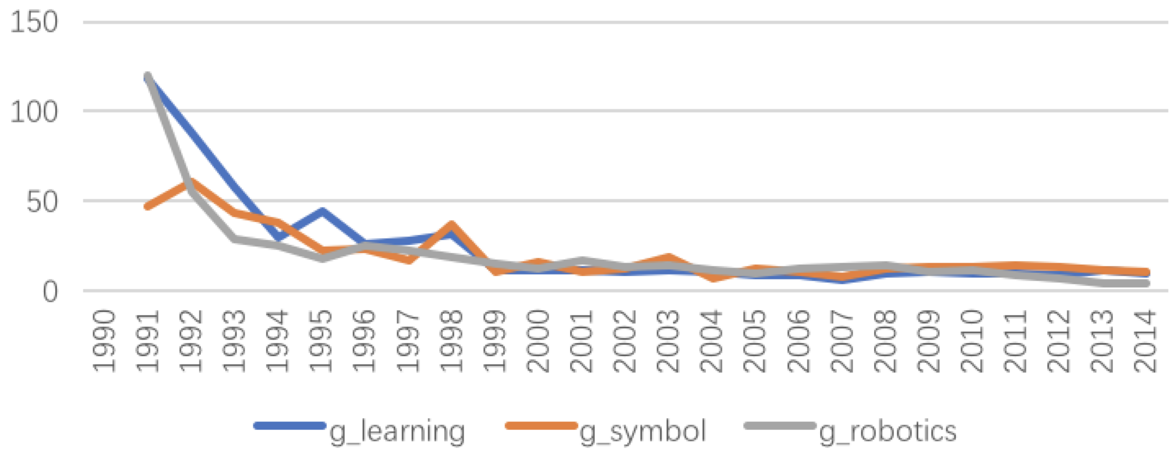


Figure 2-2. Patent stocks' growth rate of learning systems, symbolic systems and robotics

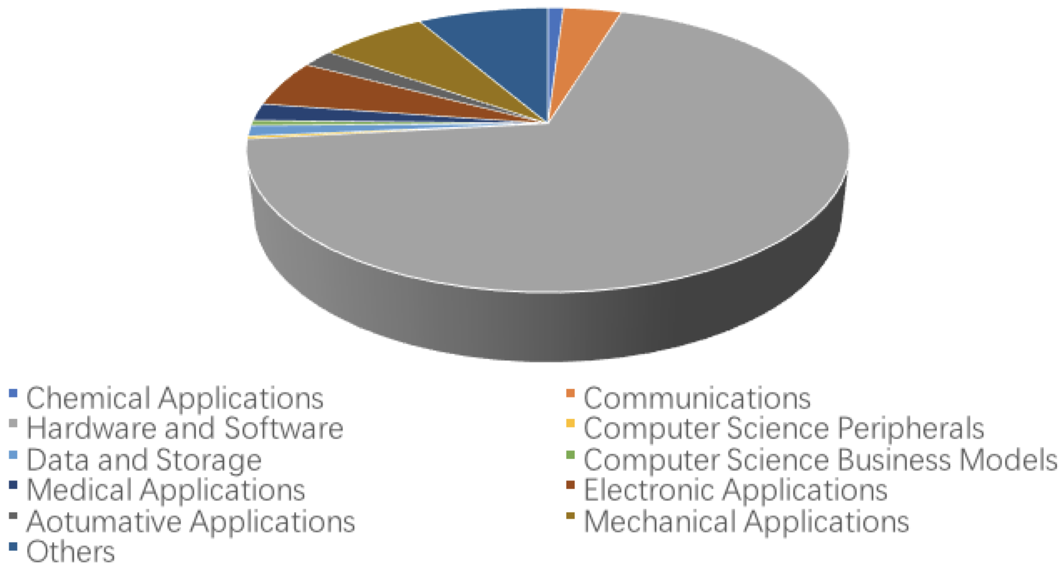


Likewise, this paper compares the AI patent distribution across sectors. Classification techniques are usually designed for administrative purposes, rather than with research in mind. Thus, Hall et al. (2001) design a more efficient classification system for the National Bureau of Economic Research (NBER) Patent Citation Data File, introducing six technological categories and 37 sub-categories. The merged patent dataset also incorporates the NBER classification, which helps the study in sector levels become more reliable and accurate. Each patent has an

NBER class and sub-class number, providing the intended application sector of patents. This paper creates a series of indicator variables for NBER sub-classifications for different sectors: chemicals patents belong to the NBER sub-classes 11, 12, 13, 14, 15, and 19; communications patents to the sub-class 21; computer hardware and software patents to the sub-class 22; computer science peripherals patents to the sub-class 23: data and storage patents to the sub-class 24; business software patents to the sub-class 25; medical patents to the sub-classes 31, 32, 33, and 39; electronics patents to the sub-classes 41, 42, 43, 44, 45, 46, and 49; automotive patents to the sub-classes 53, 54, and 55; mechanical patents to the sub-classes 51, 52, and 59, with the other fields accounting for the remaining ones.

Figure2-3 shows the proportion of AI patents across different application sectors. Computer hardware and software patents represent the majority (69 percent), similar to the 71 percent in Cockburn et al. (2018) research. Other sectors are more evenly distributed, each accounting for a small part.

Figure 2-3. Sector Distribution of patents



Observing the growth rate of patent stock for each sector, illustrated in Figure2-4, there are notable fluctuations in the 1990s. After 2001, nonetheless, it becomes relatively stable. An analysis of sector-level growth rate of AI patents provides more information when this rate is compared to the average growth of corresponding sectors for the whole patent sample. Therefore, this paper uses the historical Masterfile from Figure2-5 to calculate the average growth rate of each sector. It is apparent that there are fewer oscillations in average sector growth rate than for the AI patents. There is a decreasing trend in average sector growth rate as well. For example, the average growth rate of each sector in 2014 varies between 2 and 5 percent, while that of AI patents fluctuates between 0 and 20 percent. Figure2-6 illustrates the AI-patent and sector-average growth rates for each industry. One particular finding is that the growth rate in AI patents in the “chemicals”, “computer hardware and software”, “data and storage” and “others” sectors always outstrips the average growth rate. This finding indicates applications of AI are more popular in these sectors than in the others. However, in the case of “communications”, “business software”, and “electronic fields”, the rate of AI patents is consistently beneath average sector growth.

Figure 2-4. Sectoral growth rate of AI patent stocks

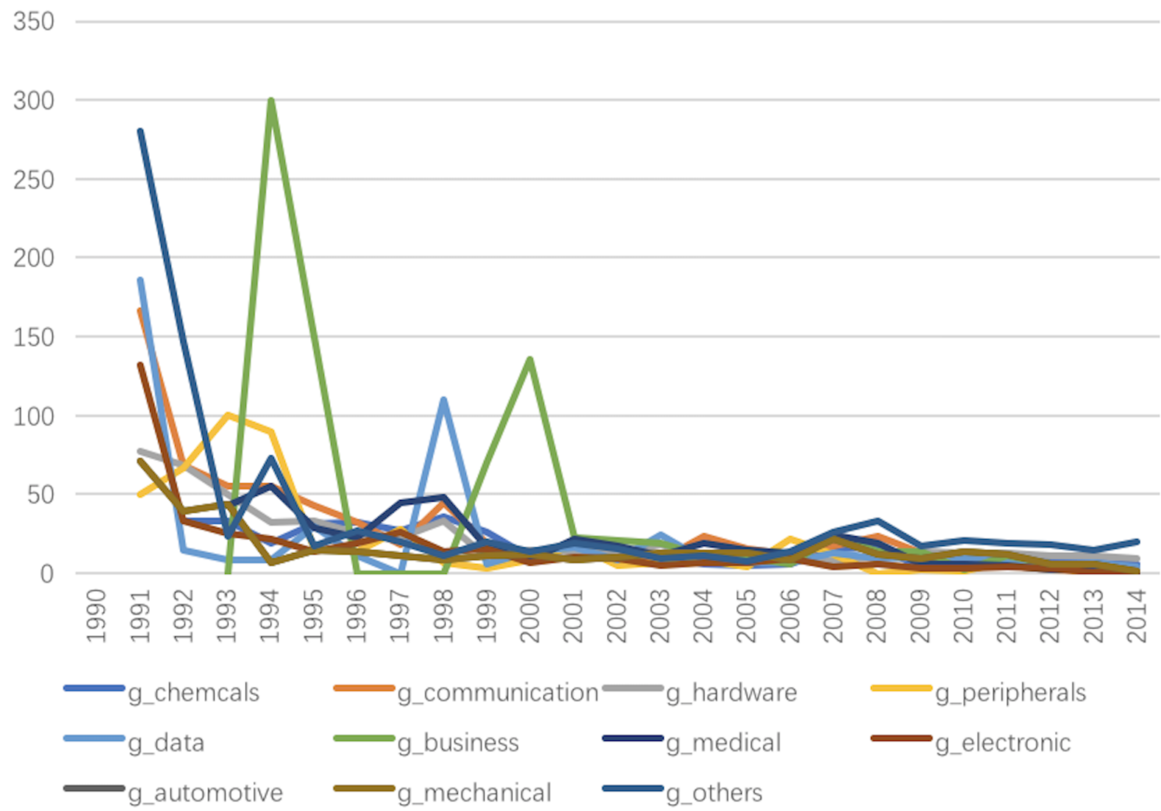


Figure 2-5. Average sectoral growth of whole patent stock

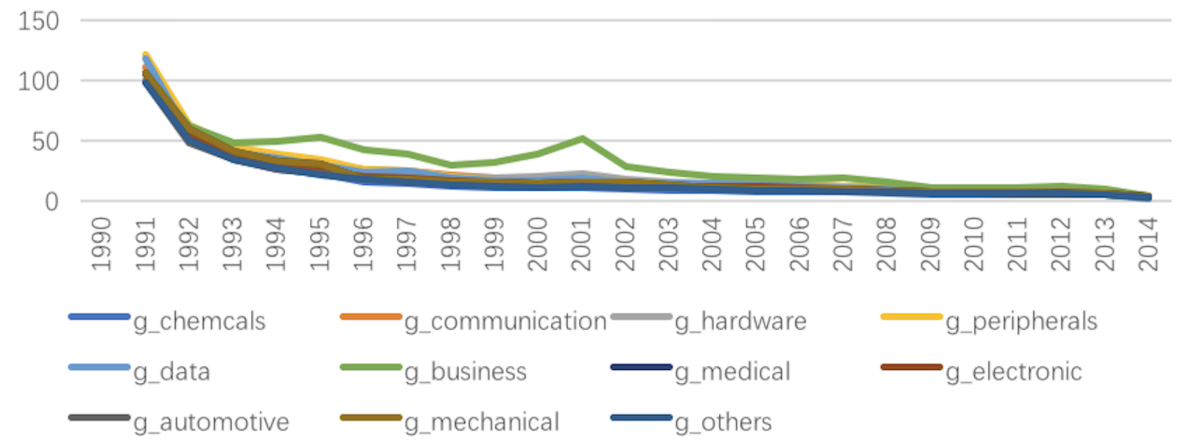
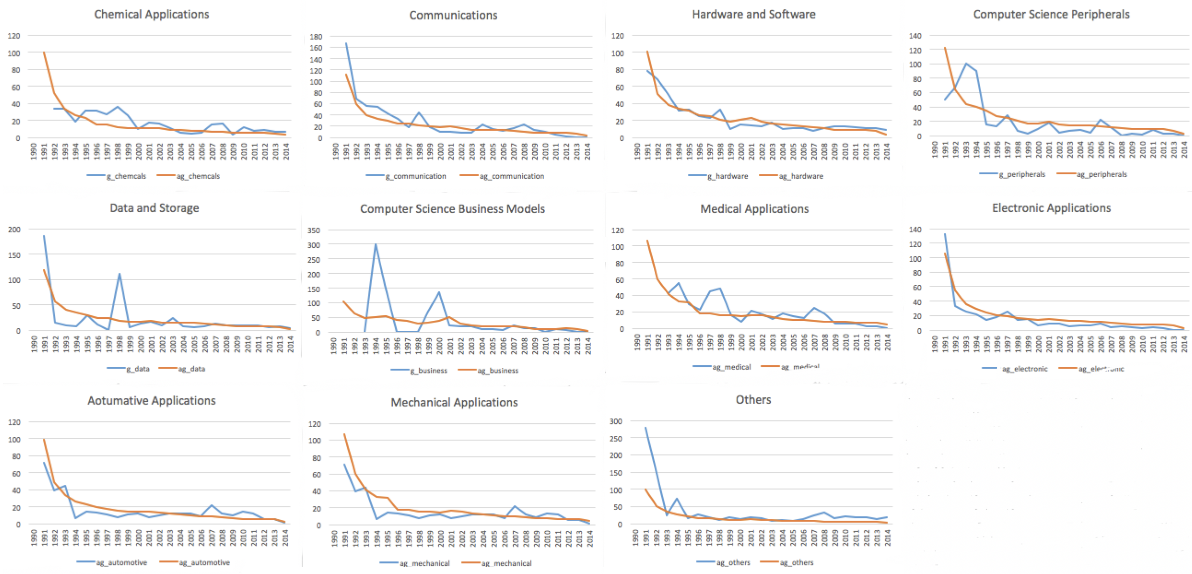


Figure 2-6. Sector average growth rate and AI patent growth rate



As the data source is the United States Patent Office, it is worthwhile to investigate whether U.S. companies have a higher share of AI patents than their international counterparts. Firstly, this paper employs two indicator variables, one for patents held by U.S. companies (domestic) and the other for those possessed by international ones (international) , based on country of patent assignee. It emerges that U.S. companies account for 69 percent of total patents and international firms for 31 percent. Figure2-7 illustrates the patent stock across domestic and international enterprises from 1990 to 2014. The blue line represents domestic firms and the red line international ones. Evidently, the blue line is always above the red one, though both are rising. Moreover, from a similar starting point, the difference between domestic and international firms has expanded since 1995. In 2007 alone, the AI patents assigned to domestic businesses were double those granted to international ones. Figure2-8 displays the domestic and international growth rate of patent stock between 1990 and 2014. The growth rate falls for both patents assigned to domestic and international firms, indeed sharply between 1990 and 1999. After this date, growth rate has been slow but steady for both.

Figure 2-7. Patent stock of domestic and international patents

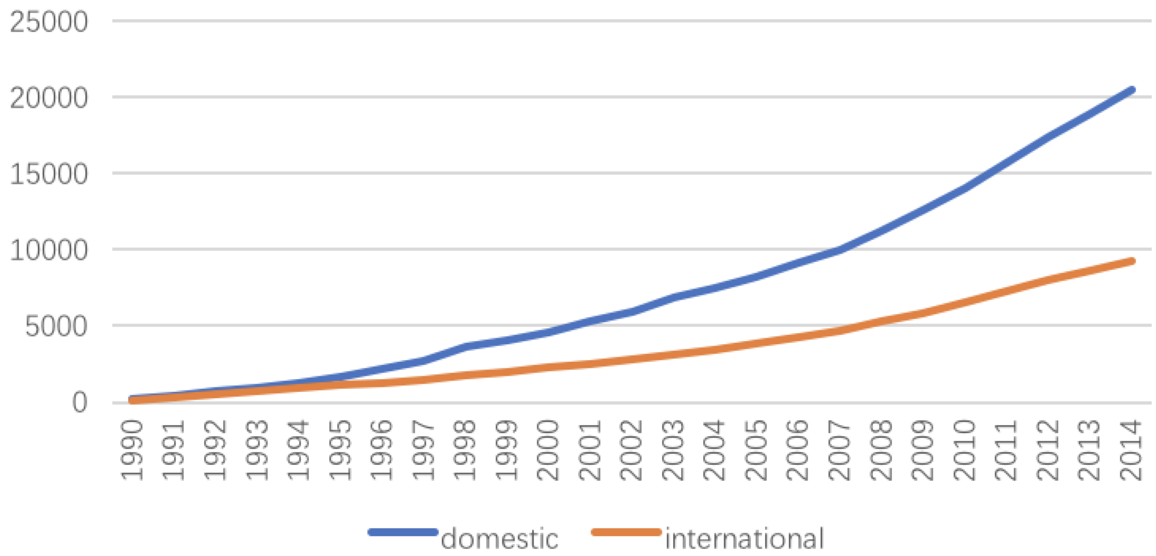
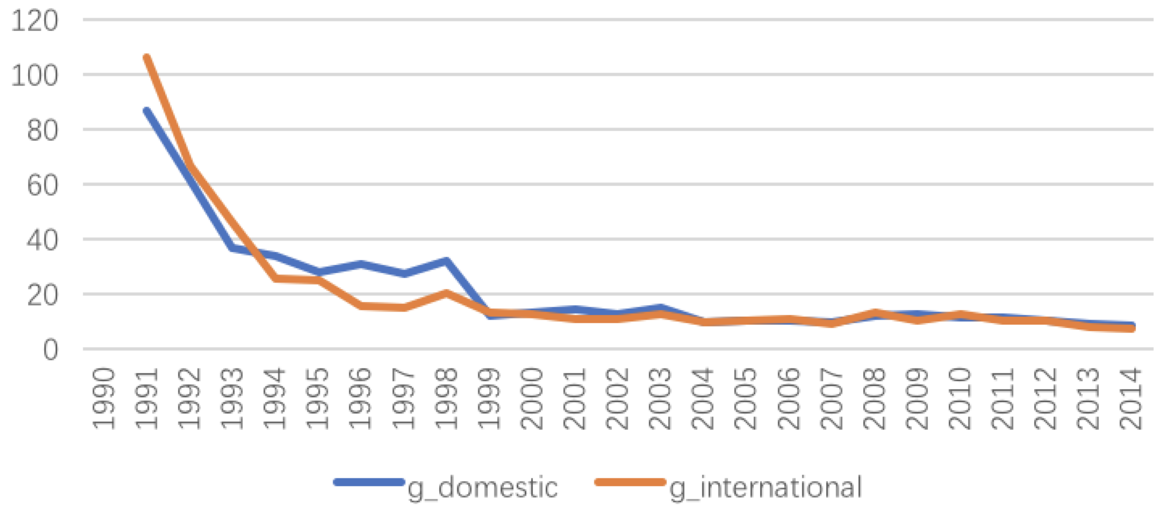


Figure 2-8. Patent stock growth of domestic international patents



Secondly, Table2-3 lists the number of patents assigned per country, reiterating the gulf the United States and the rest of the world. As mentioned, the United States occupies the biggest share (69 percent) of the total sample, with Japan (12 percent), Korea (4 percent) and Germany (3 percent) following. Based on the data quality and availability, this paper plots the time graph of patent flow and patent stock for the world, the United States, Japan, Korea, and Germany in Figure2-9 and Figure2-11 respectively. The U.S. AI patent flow matches the world trend, increasing and decreasing with it, as Figure2-9 reflects. The reason for this co-movement could be the size of the United contribution to the accumulation of AI patents globally. In contrast, the remaining countries show a relatively smooth trend without significant fluctuation. Figure2-10 depicts the patent flow growth rate of these selected countries over time, offering several important findings. The first of these is that the growth rate of all selected countries increases significantly in 2008. Similarly, all sample countries experience high growth rate in 1998, before a sharp drop.

Table 2-3. AI patent stock across countries

Country	Number of patents	Percentage
United States	20505	69.23
Japan	3636	12.28
Korea	1168	3.94
Germany	831	2.81
Canada	473	1.6
Twaiwan	381	1.29
France	271	0.91
Netherlands	254	0.86
Swizerland	252	0.85
Israel	226	0.76
China	186	0.63
Sweden	164	0.55
United Kingdom	162	0.55
Italy	132	0.55
Finland	95	0.32
Ireland	94	0.32
Singapore	63	0.21
Australia	57	0.19
India	55	0.19
England	51	0.17
Cayman Islands	45	0.15
Hongkong	41	0.14

Figure 2-9. Patent flows across countries

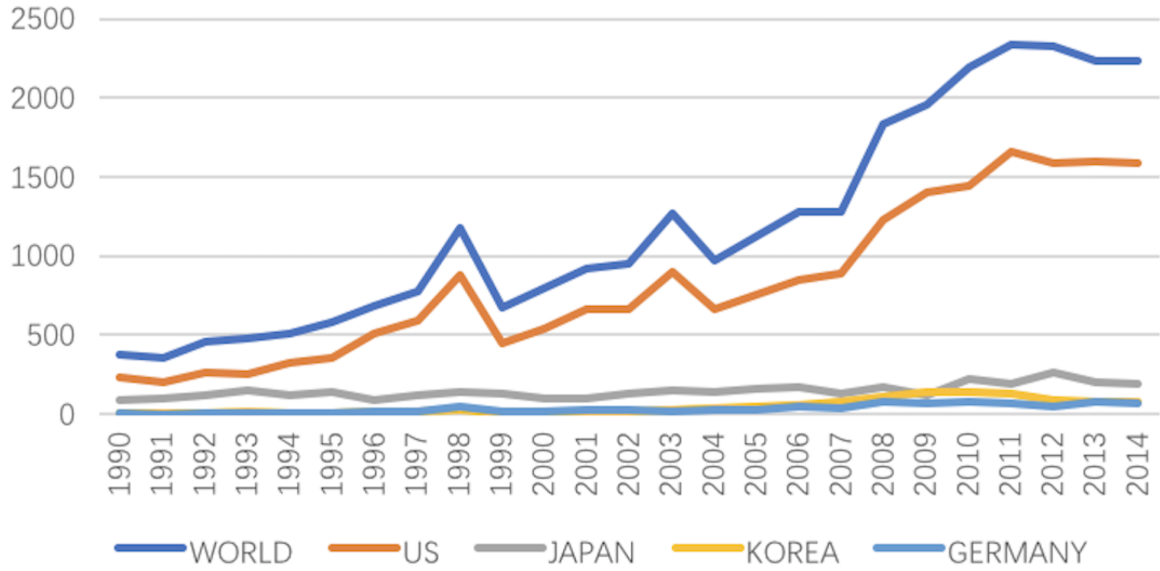
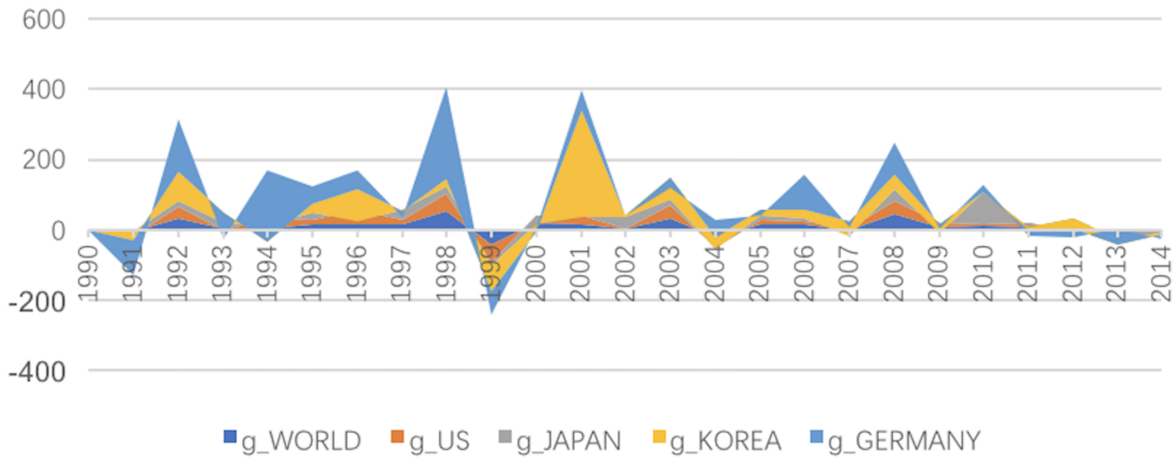


Figure 2-10. Growth rate of patent flows across countries



Turning to the analysis of patent stock changes in Figure2-11, all of the chosen countries demonstrate an increase and the United States, once again, has an apparent advantage in the number of patent stocks. Figure2-12 illustrates that the growth rate of patent stock is declining across all selected countries.

Figure 2-11. Patent stocks across countries

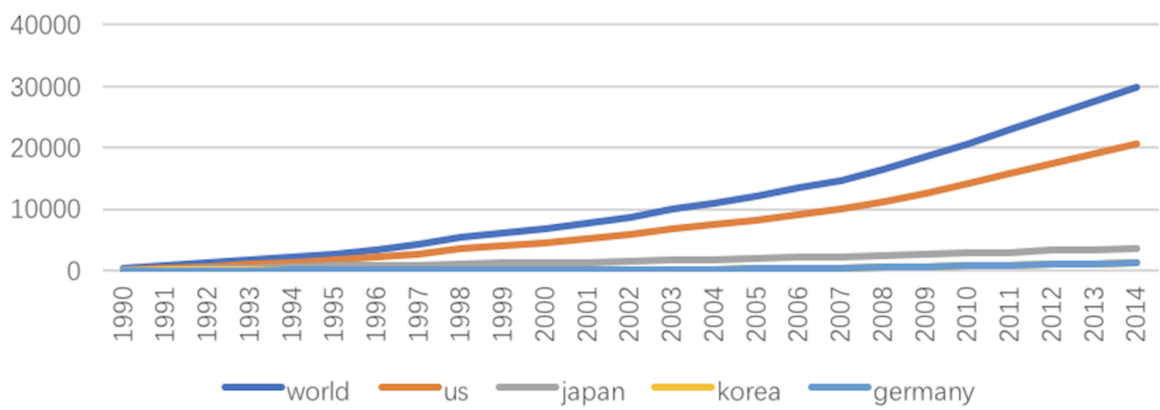
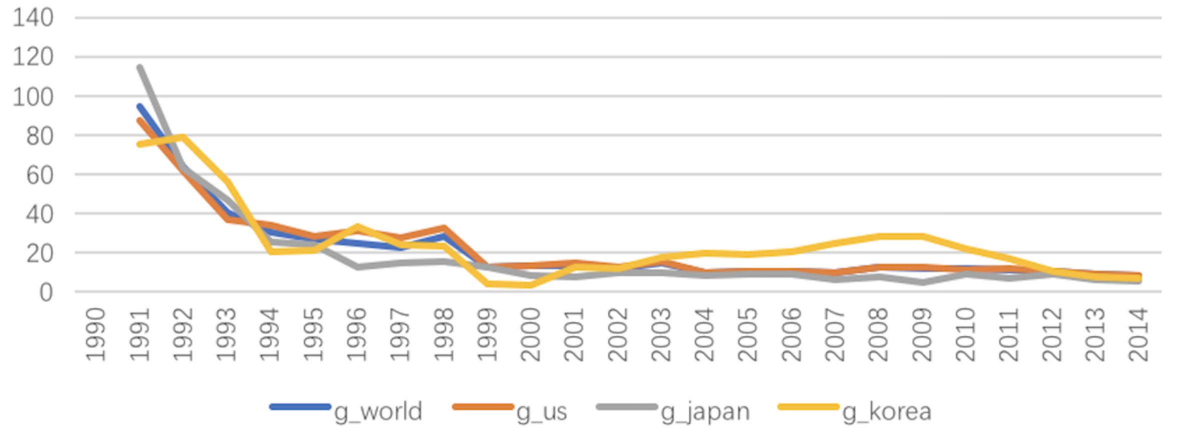
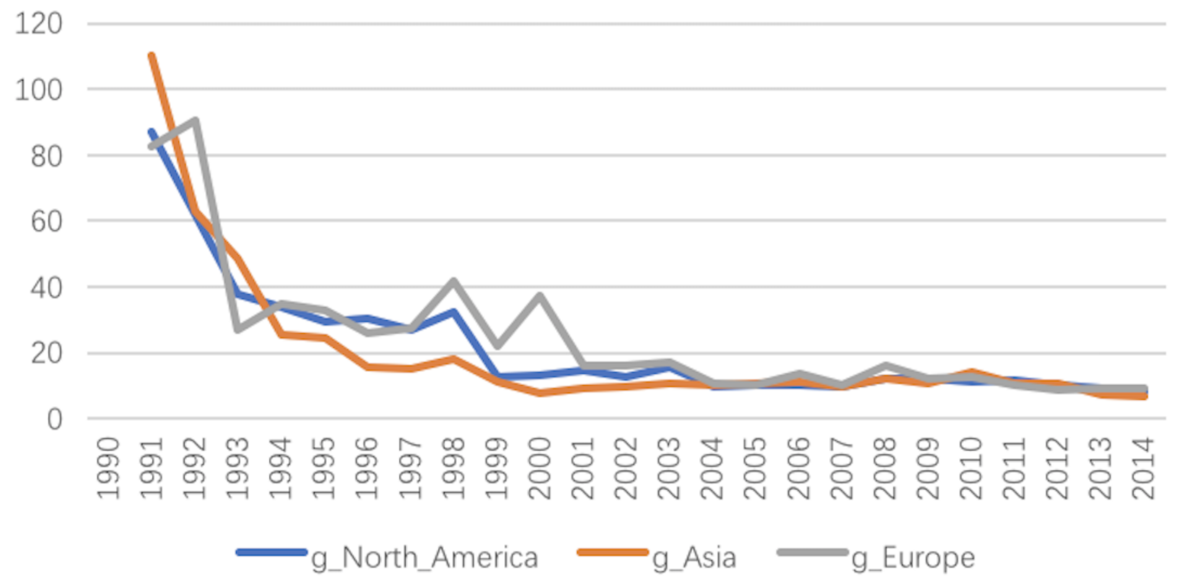


Figure 2-12. Growth rate of patent stocks across countries



In addition to the analysis of specific countries, this paper provides a continental view by sorting patents accordingly, once again by assignee country. Due to limitations to data access, only the patents of three continents can be covered (North America, Asia, and Europe), though these comprise nearly 99.4 percent of the whole sample. Demonstrated by Figure2-13, the growth rates of North America, Asia, and Europe converge. Notwithstanding that North America dwarfs Asia and Europe in terms of total patent stock number, the growth rate of patent stocks on these three continents is largely similar. The growth rate of Europe even exceeds North America in certain years, for example in 2014 (9.1 percent vs 8.4 percent).

Figure 2-13. Growth rate of patent stocks across continents



2.6 Discussion

One of the limitations of this paper may be its empirical evidence. It uses the data of artificial intelligence patents to indirectly represent the development of artificial intelligence. This could be rectified if artificial intelligence data becomes more accessible in future. Current scholarship lacks empirical evidence of the relationship between artificial intelligence and economic outcomes. Therefore, my future research interest is to probe the connection between artificial intelligence as a general-purpose technology and economic indicators, especially political stability. Politically speaking, the rapid development of artificial intelligence instills fear, for instance of job loss, which is politically destabilising. After identifying the link between artificial intelligence and political stability, the next step is to identify an appropriate data source to proxy the latter. Such statistics might be voting data from the American National Election Studies (ANES), the World Bank's political stability and absence of violence indices, or working position replacement data. Combining AI patent and the political data should provide general insight into the impact of AI on political stability. If strong correlations exist, appropriate policy suggestions can be made, before artificial intelligence becomes a general-purpose technology.

2.7 Conclusion

This paper provides a thorough, two-fold discussion of the impact the development of AI has had on the economy. Firstly, it summarizes the economic-related literature of robots, automation, and AI, both theoretical and empirical. Most previous studies focus on the effect of robotics and automation, though more recent research expresses concern at AI's impact, in so far as it could be regarded as the next general-purpose technology.

Secondly, by tracking the AI patent data from the USPTO between 1990 and 2014, it scrutinises the behavior of AI. One of the main findings is the significant increase in learning systems patents compared with those for robotics and symbolic systems, a result consistent with Cockburn et al. (2018). This supports the assumption that AI could be served as a general-purpose technology by changing the process of innovation. Moreover, this paper investigates the patent behavior based on different criteria; for example, the sector level analysis shows that the growth of AI patents in "chemicals", "computer hardware and software", and "data and storage" branches surpasses the average sector growth.

It is evidenced that AI could have sweeping ramifications for our lives and economies. The nature of these effects themselves is yet to be determined. Before AI applications fully evolve, policy makers should assess the preparedness for their introduction. For example, the adoption of AI will render certain skills obsolete, especially basic ones, which are easy to replace. In order to help workers upskill, so that they are not left behind the rate of progress, educational restructuring may be required. Companies could also provide new training for their workers. Different parts of society may need to collaborate to overcome the challenges posed by AI.

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Appendix 6B: Statement of Authorship

This declaration concerns the article entitled:			
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Publication status (tick one) **Draft manuscript** [×] **Submitted** [ ] **In review** [ ] **Accepted** [ ] **Published** [ ]			
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Copyright status (tick the appropriate statement) I hold the copyright for this material [×] Copyright is retained by the publisher, but I have been given permission to replicate the material here [ ]			
Candidate's contribution to the paper (provide details, and also indicate as a percentage)	The candidate contributed to / considerably contributed to / predominantly executed the… Formulation of ideas: - Considerably contributed to the formulation of ideas. (70%) Design of methodology: - Predominantly contributed to the design of methodology. (60%) Experimental work: - Predominantly contributed to the experimental work. (80%) Presentation of data in journal format: - Predominantly contributed to the presentation of data in journal format. (70%)		
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.		
Signed	Diling Xiang	**Date**	18/12/2020

Chapter 3

Robots and election outcomes in the United States

Abstract

The rapid development of robots and other such, labour-replacing technologies has engendered anxiety about future employment and income. The impact of robots on jobs and wages has been noticed by many commentators, though few have paid attention to the secondary effect of robots on the political economy. Ergo, this paper turns to the effect of robot usage on the outcomes of U.S. presidential and congressional elections from 2000 to 2016. To my best of knowledge, this study is the first of its kind, drawing on existing literature to assess how robots affect political indicators. U.S. industrial robot and election data form the empirical basis; European countries are used as the instrument of U.S. robot usage to circumvent endogeneity. Ultimately, the influence of industrial robots on voting outcomes in both presidential and congressional elections is deemed to be strong, though the effect is mixed for different parties and evidence of direction is lacking. The conclusion suggests that political candidates themselves might be the driving force behind robots' effect on voting outcomes. In other words, whilst the effect of robots on election outcomes is fixed, the direction may be under the sway of political leaders.

Keywords: Industrial Robots, Robot Usage, Presidential Election, Congressional Election, Voting Behavior, Political Stability.

3.1 Introduction

One of the world's eminent economists, John Maynard Keynes, predicted in the early 20th century that rapid technological development would lead to widespread "technological unemployment". Since that time, the economic ramifications of technological advances have been discussed, with particular reference to the progress of automation, robots, and AI. As Keynes' assertion implies, the main research interests have been the upshot for wages and employment.

A wealth of research attests to the negative effect of automation and robotics on income and employment (Frey and Osborne, 2013; Goos and Manning, 2007; Graetz and Michaels, 2018). Such publications have fostered fear of such technologies amongst employees. The general, economic effects of robotics are not a new topic but insufficient. The rise of industrial robots, in prevalence and capability, has an accumulation of consequences for the general economy and general economic conditions. In respect of this, many studies have already exhibited the correlation between the general economic condition and election results (Lewis-Beck and Stegmaier, 2000; Gerring et al., 2005; Aghion et al., 2007), suggesting the possibility of a transmission channel between robotics and voting outcomes and motivating its investigation. Robots and automation usually have a concomitant social cost, replacing human jobs to cause unemployment, skill obsolescence, and loss of income; such impacts on workers can threaten the power of the incumbent political leaders (Acemoglu and Robinson, 2012).

In the 2016 U.S. presidential election, the Republican victory underlines voter concern about automation. In his campaign speeches, Donald Trump, the ultimately successful candidate, chose jobs, globalization, and immigration as his thematic mainstays . As such, the research question of this paper is how robots, one kind of automation technology, affect election outcomes in the United States.

According to the International Federation of Robotics (IFR), an industrial robot is a machine that can reprogram and conduct multi-purpose tasks under automatic control. In other words, having been programmed, they perform different manual tasks without human operation, such as painting, assembling, and packaging. The reason for selecting industrial robots as the research target, from the many new technologies, is the rapid development and increasing implementation of them across the globe in recent years. The global operational stock of industrial robots tripled from 600,500 in 1995 to 1,837,524 by 2016. According to Figure3-1, the number of industrial robots per thousand workers has also soared since 1995, both in the United States and European countries. In 2016, this reached 2.3 industrial robots per thousand workers in the United States and 3.1 in Europe.

The main purpose of this paper is to detect the effect of industrial robot usage on election outcomes; the United States is selected as the empirical research object. According to the latest industrial robot data from the International Federation of Robotics, the United States accounted for 13.6 percent of the global industrial robot stock in 2016 and is the country with the most industrial robots worldwide. The popularity of robots in the United States consequences for wages and employment. If these economic effects translate to politics, this relationship will be more apparent in the United States than in other countries, which is the rationale behind the choice of the United States as the research interest. Politically, the United States has sufficient election data at the state and county level, such as from presidential and congressional elections. Both the presidential election and the congressional election in the United States will be investigated in the second paper.

This research builds on the work of Acemoglu and Restrepo (2017), who assess how increasing industrial robot usage affects employment and wages in the U.S. labour market. This paper measures changes in exposure to robots by using industry-level data of robot stock from the IFR. This is then divided by corresponding employment shares, taken from the U.S. Census, in these 19 industries, resembling Acemoglu and Restrepo's (2017) approach. The empirical work is conducted at a commuting zone level for the U.S. presidential elections and at congressional district level for the U.S. congressional elections. In addition, this paper uses the same identification strategy as Acemoglu and Restrepo (2017) to deal with the endogeneity problem. Robot exposure in the United States is instrumented by robot exposure in eight European countries, which are Denmark, Finland, France, Germany, Italy, Sweden, the United Kingdom, and Spain.

The main findings of this paper are as follows: (1) In terms of the panel regression, the increasing use of industrial robots has a negative and significant effect on the total votes of the Democrats and Republicans in U.S. presidential elections from 2000 to 2016; (2) In the panel regression, higher robot usage leads to a notably higher total of votes for the Republican party in the U.S. congressional elections from 2000 to 2016; (3) In the cross-sectional regression of the U.S. presidential elections, the increase in industrial robot stock affects the weighted total votes of the Democrats negatively and the weighted total votes of the Republicans positively for six states, with high robot density between 2012 and 2016. All these results suggest the correlation between robot usage and election outcomes; the increasing use and rapid development of robots influences voting in the United States. Though these findings are mixed for different parties, the impact of robots on election outcomes may be fixed and the direction could be affected by the behaviour of political leaders. A possible explanation for this is that industrial robots are steadily replacing human jobs, causing people to worry about their employment and wages. Therefore, the attitude of political parties towards employment, outlined in their campaign declaration, plays a key role in voter decision-making. Parties offering employment protection policies may attract more voter-support than others.

Further robustness checks verify the significant effect of robot exposure on U.S. presidential election outcomes. Firstly, this paper excludes the robot data of the automotive industry, which has the highest robot density in the specification of robot exposure. Secondly, it adds the robot exposure of the automotive industry as one of the control variables. Under these two adjustments, robot exposure still has a significant and negative impact on the total votes of the Democrats in the U.S. presidential election, which is consistent with the baseline result of the Democrat votes.

The remainder of this paper is organized as follows. Section 3.2 presents the literature review of general economic conditions and election outcomes, highlighting how the scholarly gap between robot usage and elections is bridged. Section 3.3 explains the empirical specification of the model, the construction of the main variables used in the regression, and the methodology of the empirical regression. Section 3.4 introduces the data source for each of the empirical-analysis variables and interprets the correlation between the robot exposure in the United States and eight European countries at the industry level, which is the foundation for the first- and second-stage regressions. The regression results of robot exposure on presidential elections in the United States are obtained by using a pooled model, a fixed effect model, a random effect model, and an IV model, as discussed in section 3.5. Section 3.6 presents the empirical results of robot exposure on U.S. congressional elections. Section 3.7 discusses the cross-sectional analysis of U.S. presidential election in sub-periods. Section 3.8 presents the robustness check of the baseline regression result for the presidential and congressional elections. The final section is the conclusion and discussion, which summarizes the main findings of this research.

3.2 Literature of general economic conditions and elections

From public officeholders to academics , the general economic conditions are considered crucial to election outcomes. Sometimes, lower unemployment and lower inflation rates are said to benefit the incumbent. If the unemployment and inflation rates are high, challengers have the advantage. Some have argued, more specifically, that an increasing unemployment rate benefits the Democrats, whereas an increasing inflation rate favors the Republicans. Politicians and their advisers make painstaking efforts to ensure good economic conditions. For example, Republican Richard Nixon's 1972 victory is almost solely ascribed to the serious inflation issue of 1971. In addition, Wright (1974) highlights the influence the intention to provide New Deal spending programs had on the electorate. According to Okun (1973), one previous chair of the Council of Economic Advisers agrees with the proposition that the general condition of the main economic variables is a key determinant of election outcomes. Certainly, politicians try to create better aggregate economic conditions for electoral success, and yet the effect of these aggregate economic variables is uncertain. Indeed, policy makers ascribe to the traditional wisdom that changes to the economic condition alter voting behaviour, though some analysts remain undecided as to the relationship between the two. In the past four decades, many have put this assertion to the theoretical and the empirical test.

The section to follow covers the literature of this field, summarising evidence of the link between economic conditions and election outcomes, before turning to investigations into the economic effect of robotics.

3.2.1 Literature of how the economic conditions affect the voting choices of people

The influence of the economy on election outcomes is not as straightforward as the conventional theory of reward and punishment. In theory, voters consider past economic performance as indicative of the economic competence of incumbent. If the economy is doing well, voters tend to vote for the government. Conversely, they are more likely to vote against the incumbent when it underperforms. Tufte (1975) demonstrates that economic conditions influence the election outcome. Ferejohn (1986) agrees that a strong economy has its electoral reward for the party in office. Evans and Andersen (2006), moreover, highlighting a lack of willingness and ability amongst voters to process complex policy information, declare that the economy, as the most intelligible barometer, is most commonly chosen to evaluate government performance. By implementing the reward-punishing strategy, voters provide incentives that solve moral hazard problem between elected officials and citizens, contributing to select the compete policymaker(Duch and Stevenson, 2008).
The reward-punishing theory is based on the political business cycle, which stipulates appropriate fiscal policy stimulates the economy and boosts the supply of public goods. Therefore, by using expansionary fiscal policy, the governing parties can promote growth and be rewarded with re-election. Brender and Drazen (2005), however, question the ability of the incumbent government to implement economic chance. They also cast doubt on the idea that fiscal expansion can directly promote economic development. Among different governments or electoral systems, an aggressive budget deficit reduces the chance of re-electionAlesina et al. (1997), in their empirical study of the United States, also point to an often disfunctional political business cycle. By examining the direct effect of fiscal policy on re-election, Drazen and Eslava (2010) claim that voters tend to punish, rather than reward governing parties who implement a loose fiscal policy.
Moreover, economic performance is hard to evaluate. It is commonly assumed that economic outcomes are mainly driven by objective, macro-economic indicators (Tverdova, 2012). However, Evans and Andersen (2006) contend that voters are more likely to subjectively evaluate economic performance and hence the incumbent vote is influenced by voter perceptions of the economy. Gerber and Green (1999) observe that political preconceptions even lead to different conclusions being drawn from the same evidence. Most respondents to the survey of Michelitch et al. (2012) confirm that their personal assessment of the economy plays an important role in their choice of party and candidate. Voters analyse the objective

economic outcomes before making a decision based on this analysis (Becher and Donnelly, 2013). In this way, individuals from different backgrounds make different inferences from the same objective data.

Lewis-Beck and Stegmaier (2000) acknowledge that partisan orientation shapes economic perception. Voters tend to see and accept that which assimilates to their pre-determined values. Thus, political partisanship conditions public perception of economic performance and management competence. Bartels (2002) emphasises that these partisan loyalties are a more comprehensive determiner of voting decision, in so far as they pertain to the perception of all political matters, not only the economic ones. Duch et al. (2000) assert that economic perception varies according to income level and employment status. Similarly, Nannestad and Paldam (1994) note that individual evaluations of the economy are defined by what that person has won or lost, or stands to lose or gain. Objective economic outcomes vary in importance to voters from different social classes and economic sectors. A worker who has lost their job does not see economic overperformance, even if GDP per capita has skyrocketed in the last year. Conversely, a worker within a fast-growing industry has cause for optimism, even during an economic downturn.

By established logic, voters are highly likely to cast their ballot in accordance with past economic performance. Notwithstanding this, Alesina et al. (1997) discover that voters often focus on future economic fortunes. The public compares the policy proposals of the various parties and infers economic competence from the potential economic efficacy of that suggested. Bartkowska and Tiemann (2015) concur that voters vote for the incumbent if they envisage an economic boom within the next 12 months, otherwise preferring the opposition party. Voters seek economic growth in the next administration period, which is why future economic policies also matter.

Furthermore, the effect of economic performance on election outcomes differs depending on circumstance. As Evans and Andersen (2006) observe, political conditions determine the extent of the economy's electoral influence . In less developed economies, which are often new democracies, strong economic improvement, such as a steep growth in GDP per capita, corresponds with an especially high probability that the governing party will do well at the polls. However, the positive correlation between economic prosperity and re-election is weaker in developed countries. Soroka (2006) also finds that the degree of influence economic performance has on election results varies, principally because of the economy's inherent instability. During economic crises, the media provides more economic coverage, for instance. Even small economic changes, in such scenarios, can substantially alter voter choice.

Moreover, surveying the 2009 and 2014 European parliament elections, Okolikj and Quinlan (2016) do also not detect a straightforwardly linear relationship. While voters paid more attention to the economy in 2009, they had shifted their focus to the economic responsibility of national government by 2014.

3.2.2 Literature of empirical studies between general economic conditions and congressional election

Kramer (1971) is the first to calculate the multivariate regression between congressional election results and aggregate economic variables. He uses the share of Republican votes in elections between 1896 and 1964 as the explained variable, whilst the explanatory variables are unemployment rate, real income per capita, consumer price index, and incumbent party et al. One of Kramer's principal discoveries is that unemployment rate exterts little or no effect on congressional election outcomes, whilst changes to real income and inflation do. Though Kramer's research is systematic, he is challenged by Stigler (1973) who conducts adapts Kramer's methods in several ways. The first of these is moving from a one-year variation of aggregate economic variables to a two-year variation. The second change is the extension of the time period and the third is to include the war years (1918, 1942 and 1944). Stigler (1973) exhibits the sensitivity of Kramer's results to these alterations, which leads him to dispute the notion that real income per capita influences elections.
Arcelus and Meltzer (1975) succeeding study gauges the effect of general economic conditions on congressional elections between 1896 and 1970. Unemployment, it is deduced, is irrelevant, though the consumer price index gives some indication. Arcelus and Meltzer (1975) contends that changing economic conditions are mainly reflected in the turnout rate, noticing a connection between improving economic conditions and a higher turnout rate. Unlike Kramer (1971), Stigler (1973), Lepper (1974) and Arcelus and Meltzer (1975) submits that increasing unemployment reflects negatively on the incumbent congressman. One reason for this disparity could be the exclusion of real income from Lepper's regression, whereby the effect of real income is captured by unemployment. Tufte (1975) also rejects Stigler's findings by combining congressional performance data and economic conditions. In Tufte's work, real income clearly influences congressional election results. Goodman and Kramer (1975) conclude that the weight of evidence points towards aggregate economic variables affecting congressional regression results, though others have challenged their empirical techniques.
The performance of the incumbent party is also a commonly discussed determinant of voter behavior. The economic retrospective voting model says that voters consider the economic performance of a party, an officeholder, or the administration when casting their ballot. One assumption of this model is that voters care more about the outcome and performance of policies, rather than the policy itself. Fiorina (1978) uses election survey data from 1956 to 1974 to test the notion of economic retrospective voting. He/she finds little evidence in support of the novel, corroborating that economic performance of the incumbent party impacts voting behaviour. Arcelus and Meltzer (1975) claim that the upshot of general economic condition is to be seen in voter turnout rather than preference. Fiorina (1978) examines the correlation between turnout rate and economic conditions, implementing "vote" as the dummy variable and "not vote" as the explained variable, but detects no correlation

between the two.
Later studies on U.S. congressional election surveys still support the effect of economic conditions. Brown and Woods (1991) find significant retrospective economic effects on voters' choices in the U.S. congressional election. Romero and Stambough (1996) report the retrospective economic indicators can affect voters' decision on reward or punish candidates of the incumbent party. Locerbie (1991) also finds significant effect of retrospective and prospective economic variables by using the data of U.S. congressional elections from 1956 to 1988. It seems that the economic variables establish the proposition on congressional elections, and in turn move voters to punish the president's party at economic recessions and reward it at economic progress (Lewis-Beck and Stegmaier, 2000).

3.2.3 Literature on empirical studies of general economic conditions and presidential elections

In addition to discussions of congressional elections, the link between the economy and presidential elections has also been subject to scholarly scrutiny. There are different views on the effect of income inequality on voting, especially in regard to turnout. Some believe that increasing inequality leads to increased electoral participation, whereas other insist that rising inequality reduces political engagement.
Bernanke et al. (2007) notes the explosion of wage and income equality in the United States since the 1960s. The growing income inequality usually comes with decreasing income of lower-class people, and also leads to a bad political environments for the lower-class individuals (Brady, 2004). For lower-income voters, the function of government is to alleviate inequality and so, in order to improve their social reality, they become political active. Though Brady's statement seems reasonable, the opposite may be true in reality. Rising inequality might actually result in political apathy, whereby the upper-classes are disinterested in their prosperity and the lower-classes lose faith in the capability of government to resolve social difficulties. The problems of poverty, unemployment, and economic depression deteriorate class relations and the mental health of individuals; thus, increasing inequality is accompanied by a decline in political engagement (Rosenstone, 1982). Putnam (2001) and Widestrom (2006) also submit that motivations for civil participation diminish and so too voting turnout when society is unequal. Moreover, Piven and Cloward (1988) state that class contradiction, caused by increasing inequality, can restrict the voting access of the lower-classes. As the latter account for the majority of the population, turnout will surely drop.
What is the link between inequality and voting behavior? Voters cannot directly observe inequality , thus it is difficult to gauge. It has been suggested that a more unequal society in the United States would benefit the Democrats. Edsall (1985) highlights that the Democratic

party is a broad church. The association between inequality and voting behaviour has also been viewed through the lens of class. If a society is more unequal, the share of lower-class voters, who are interested in intervention policies that promote the redistribution of wealth, will increase. At the same time, the proportion of middle-class voters falls, those who have already received benefits from the state and are not interested in restricting the welfare system .

For empirical evidence, Galbraith and Hale (2008) selects state-level U.S. presidential election data from 1969 to 2004 to investigate the relationship between income inequality, voter turnout, and party preference. Galbraith, employing a fixed effect estimation, discerns that increasing income inequality is correlated with declining voter turnout and Democratic success.

Having considered the United States, this paper also assesses the situation in OECD countries. Judging by a World Value Surveys study between 2005 and 2007, there is less tolerance of inequality in European countries than in OECD countries on other continents. Most respondents in the EU have a negative attitude towards inequality in their countries. The policies and commitment of political parties to shrinking inequality vary, though left-leaning parties prefer direct action. On the theoretical side, Coughlin (1986) proposes that every political candidate has a different reputation for redistributing income according to the reputational effect model. According to the preference of income redistribution, voters will choose the candidate who has a corresponding reputation. For instance, Palmer and Whitten (2011) and Alesina et al. (1993) argue that the Democratic party has a better reputation on high inflation and low unemployment than the Republicans. On the empirical side, Pontusson and Rueda (2010) demonstrate that widening income inequality in OECD countries induces parties on the left to employ more redistribution policies. In addition, Bermeo and Bartels (2014) discern that voters become more reactive to macroeconomic policy when the incumbent party is left-leaning. Though rising inequality is itself enough to attract academic comment, many researchers look more specifically at its electoral ramifications. Bouvet and King (2016) addressing this literature gap, inspect the data of 32 OECD countries from 1975 to 2013, deducing that economic growth is the most robust determinant of voting behaviour. Moreover, the share of left-leaning parties decreases when income inequality rises within a normal economic backdrop. Nevertheless, the share of votes for left-wing parties increases when rising income inequality and unemployment exist during economic recessions. During such economic downturns, voters become more tolerant of higher government spending to redress inequality and unemployment.

3.2.4 Literature of robot-impact on general economic conditions

The economic effect of robot density has been widely discussed and there is a great deal of evidence characterising the association between them. Graetz and Michaels (2018) evidence the correlation between industrial robots and several economic variables; for instance, increasing robot usage leads to higher labor productivity and value added per worker. Acemoglu and Restrepo (2017) shows that robot density affects employment and wages negatively and significantly in the United States; the robustness of this result is ratified. However, there is a notable absence of research into the direct impact of robot usage on election results, an omission this paper seeks to rectify. It is the first to probe the link between industrial robots and U.S. elections, distinguishing it from previous studies.

3.3 Data description and first stage

This paper aims to investigate how industrial robots affect the election outcomes in U.S. presidential elections and U.S. congressional elections between 2000 and 2016. For the presidential elections, this paper samples 742 commuting zones in the United States; these are commonly used in demographic and economic analyses. Commuting zones includes all metro and non-metro areas in the United States, which can show the diversity in economic and social characteristic of non-metro area. For the congressional elections, this paper samples 435 congressional districts in the United States. The aim of this section are as follows. Firstly, defines and sources the variables used in the empirical study. Secondly, introduces the construction process of change to robot exposure. Thirdly, explains the first-stage correlation between the instrument that uses the exogenous change in robot exposure in European countries and the U.S. exposure to robots.

3.3.1 Dependent Variables: election outcomes

The dependent variable refers to a set of election outcomes in the U.S. presidential and congressional elections from 2000 to 2016, which comprises the change in total Democrat votes ($DEMO$), the change in weighted Democrat votes ($DEMOPW$), the change in total Republican votes ($REPUB$), the change in weighted Republican votes ($REPUBPW$), the change in the share of Democrat votes to the sum total votes ($SDEMO$), and the change in the share of Republican votes to the sum total votes ($SREPUB$). Weighted Democrat/Republican votes is calculated by using the total Democrat (Republican) votes over the total population. The Share of Democrat (Republican) is calculated by using the total Democrat (Republican) votes over the sum of total Democrat votes and total Republican votes. The voting data for the U.S. presidential elections comes from the Federal

Election Commission and the voting data for the U.S. congressional elections is sourced from the MIT election lab.

3.3.2 Independent Variables:robot exposure

The most important independent variable is the change in robot exposure in the United States (ROBOTUS). Exposure to robots is gauged by data of the U.S. industrial robot stocks in 19 industries from the International Federation of Robots (IFR) and corresponding employment share figures from the United States census. This measures the adoption of industrial robots across the U.S. commuting zones. The expression of changes in exposure to robots is shown as follows:

$$ROBOTUS = \sum_{i \in \mathcal{I}} \ell_{ci,t} \left(\frac{R^{US}_{i,t+4}}{L^{US}_{i,t}} - \frac{R^{US}_{i,t}}{L^{US}_{i,t}} \right) \tag{1}$$

where $\ell_{ci,t}$ means the share of employment of industry i in commuting zone c over the total baseline employment and $\left(\frac{R^{US}_{i,t+4}}{L^{US}_{i,t}} - \frac{R^{US}_{i,t}}{L^{US}_{i,t}} \right)$ shows the change of industrial robots in one election period (4 years). This paper first uses data from the County Business Patterns (CBP) to compute the percentage of employment by industry for each commuting zone ($\ell_{ci,t}$). The IFR robot data, collected from surveys of robot suppliers, covers nearly 90 percent of markets deploying industrial robots . The IFR has published statistics of industrial robot variation by industry between 2000 and 2016; these encompass the United States and eight other European countries (Denmark, Finland, France, Germany, Italy, Sweden, the United Kingdom, and Spain), which represent the exogenous change of robot exposure. The IFR classifies robots into 19 industries, which are agricultural; forestry and fishing; mining; food and beverages; textiles; wood and furniture; paper; plastic and chemicals; glass and ceramics; basic metals; metal products; metal machinery; electronics; automotive; other vehicles; other manufacturing industries; utilities; construction; education; research and development; and other non-manufacturing industries. By combining robot and employment data at the industry level from EUKLEMS and USKLEMS, the number of robots per worker can be generated. Finally, exposure to robots is calculated by adding up the product of employment share and robot per worker by industry for each commuting zone. However, fluctuations in robot adoption in one industry may be related to trends in other industries or special political conditions in an industry or commuting zones; this could obfuscate the relationship between robot exposure and political outcomes. To account for this, this paper constructs an instrument to proxy the exogenous change in robot exposure in the United States, echoing replicating the approach of David and Dorn (2013); Bloom et al. (2016); Acemoglu and Restrepo (2017). The change in robot exposure for each election period between 2000 and 2016, in the aforementioned eight European countries, illustrates robot development on the world stage and is the proxy of industry trends in the United States.

3.3.3 Control Variables

Control variables can be divided into three main categories. The voting behavior and pattern shows great diversity in different demographic dimensions, which also may be associated with differences in the robot exposure. Therefore, we control a set of demographic variables: total population; working age population (WORKING); Black population (BLACK); Hispanics' population (HISPANICS); the percentage of adults with less than a high school diploma (EDUC1); the percentage of adults with only a high school diploma (EDUC2), and the percentage of adults with a bachelor's degree or higher (EDUC3). As the manufacturing sector has the vast majority of robots application, we want to ensure that the estimated effects of robot exposure does not capture the possible trends in manufacturing and other industries. Thus, this paper control a set of industry related variables: total employment, in the construction (CONSTRUCT), manufacturing (MANUFACT), and non-tradable sectors (NONTRADE), as well as the proportion of routine jobs (ROUTINE). Along similar reasons, the change in robot exposure may has correlation with differences in import competition of commuting zones. This paper further controls the U.S. imports from China (IMPORTCN), which follows the similar approach of Acemoglu et al. (2016). Table3-1 presents and details the data sources for all regression variables.

Table 3-1. Explanation and data sources of all variables

Variable Name	Definition	Data Source
DEMO	Changes in total votes of democratic party in two continuous presidential election	Federal Election Commission
REPUB	Changes in total votes of republican party in two continuous presidential election	Federal Election Commission
DEMOPW	Changes in total votes of democratic party in two continuous presidential election weighted by commuting zones' population	Federal Election Commission
REPUBPW	Changes in total votes of republican party in two continuous presidential election weighted by commuting zones' population	Federal Election Commission
SDEMO	Changes in the share of democratic's votes to the total votes of democratic and republican party	Federal Election Commission
SREPUB	Changes in the share of republican's votes to the total votes of democratic and republican party	Federal Election Commission
ROBOTUS	Changes in exposure of robots in US	IFR, USKLEMS, EUKLEMS, CBP
ROBOTEU	35th percentile of changes in exposure of robots among European countries	IFR, USKLEMS, EUKLEMS, CBP
POP	Total population of commuting zones	United States Census
WORKING	Population at working age of commutinf zones	United States Census
BLACK	Black population of commuting zones	United States Census
HISPANICS	Hispanic population of commutinf zones	United States Census
EDUC1	Percent of adults with less than a high school diploma	United States Census
EDUC2	Percent of adults with a high school diploma only	United States Census
EDUC3	Percent of adults with a bachelor's degree or higher	United States Census
CONSTRUCT	Employments of construction industry of commuting zones	County Business Parterns (CBP)
MANUFACT	Employments of manufacturing industry of commuting zones	CBP
NONTRADE	Employments of non-tradable industry of commuting zones	CBP
ROUTINE	Share of employment in routine jobs	CBP
IMPORTCN	Share of imports from China to the United States	UN Comrade Database

3.3.4 Instrument Variables: EU robot exposure

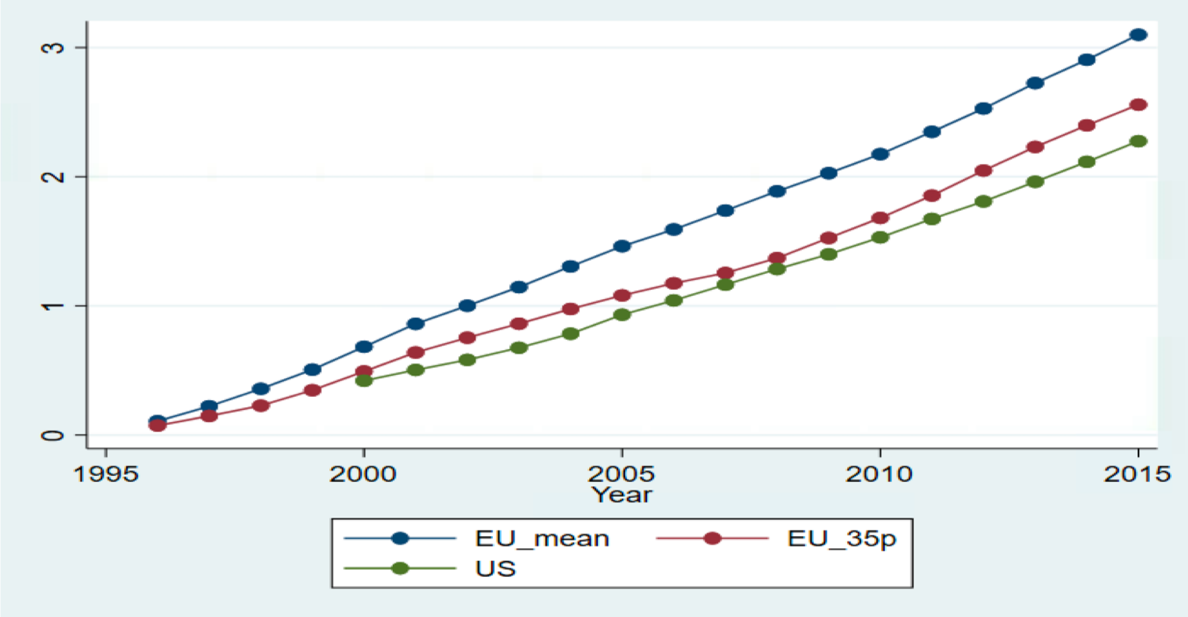
As discussed in the previous context, the estimated impact of robot exposure may be biased due to omitted variables, such as local economic shocks. Though our rich controls could mitigate this concern, we can not control all sources of unobserved effects. In order to deal with the endogeneity of robot exposure, we develop an instrument by using the robot exposure of European countries as the exogenous change of U.S. robot exposure. A good instrument should satisfy two requirements. Firstly, instrument exclusiveness, the instrument should not be correlated with the error term. This paper proxy the robot developments in the world technology frontier as the instrument for industry trends of robots in the United States. The United States does not shape the world technology frontier of robots. This strategy allows us to concentrate on the changes that results solely from sectors in which the use of robots has been concurrent in most advanced countries.

Secondly, instrument relevance, the instrument should be correlated with the U.S. robot exposure. Figure3-1 shows the time variation of the average and 35th percentile of industrial robots per thousand workers in the previously named eight European countries. This figure also adds robot usage in the United States as a comparison. The mean robot density in European countries starts at 0.7 robots per thousand workers in the early 2000s and rises quickly to almost 3 robots per thousand workers by 2010. In the United States, robot usage, though on a slightly smaller scale, follows a similar trend; it begins around 0.4 robots per thousand workers and expands to around 2 robots per thousand workers by 2010. Moreover, the United States follows the same pattern as the 35th percentile of robot density across the sample European countries. Based on these findings, this paper constructs the instrument of the U.S. robot exposure in the following way:

$$ROBOTEU = \sum_{i \in \mathcal{I}} \ell_{ci,t} \left(p_{35} \left(\frac{R_{i,t+4}}{L_{i,t}} \right) - p_{35} \left(\frac{R_{i,t}}{L_{i,t}} \right) \right) \tag{2}$$

As before in Equation(2), $\ell_{ci,t}$ indicates the employment share of industry i in commuting zone c, and $\left(p_{35} \left(\frac{R_{i,t+4}}{L_{i,t}} \right) - p_{35} \left(\frac{R_{i,t}}{L_{i,t}} \right) \right)$ denotes the 35th percentile of industrial robots per thousand workers across the sample European countries. The reason for using the 35th percentile is the similarity and closed between the U.S. and 35th percentile curves, as depicted in Figure3-1.

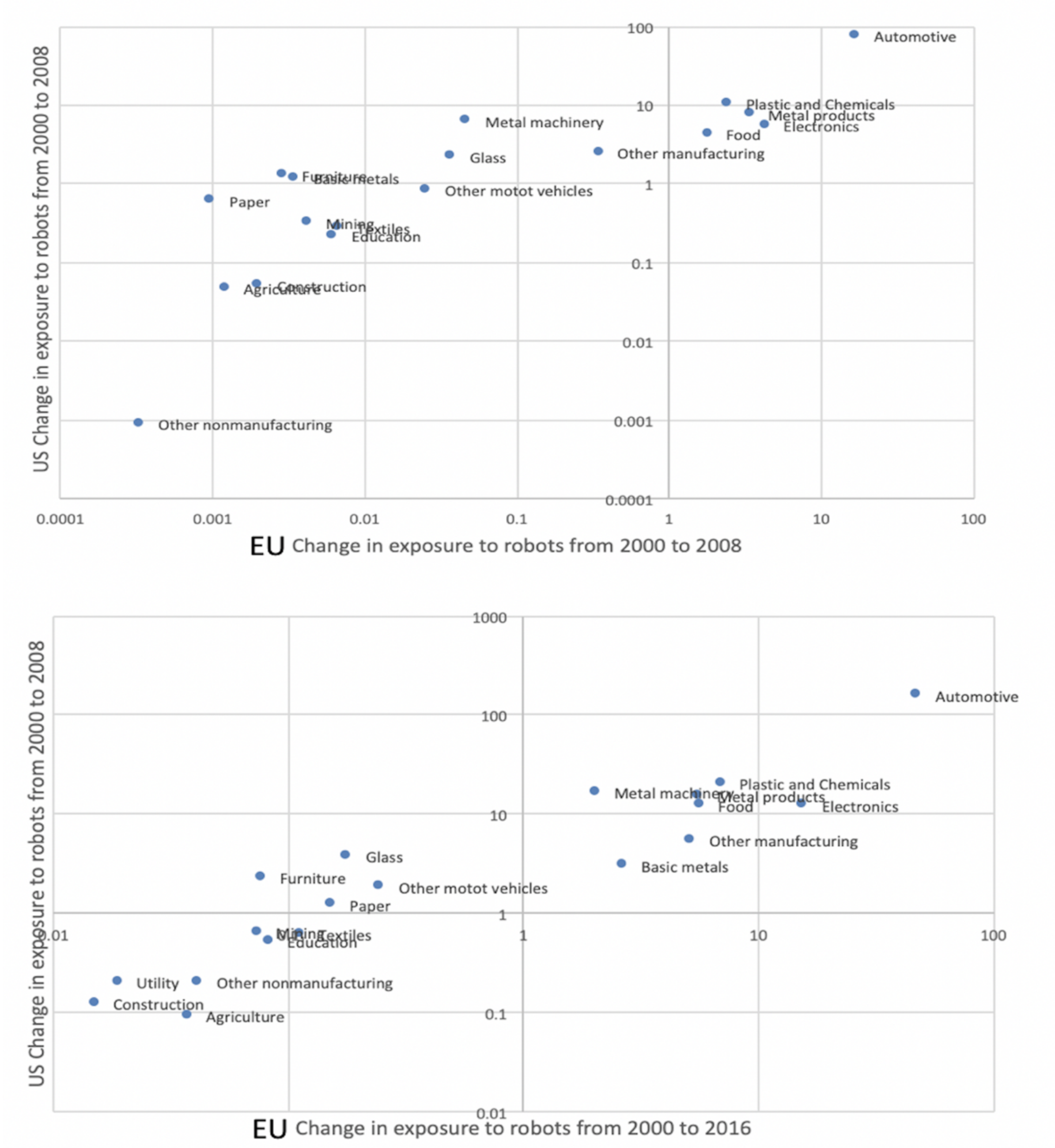
Figure 3-1. Industrial robots per thousand workers in the United States and Europe. The blue line means the average in Europe; the red line represents the 35th percentile in Europe and the green line represents the United States.



Though U.S. and European robot exposure move in the same direction, this paper uses industry level robot usage in its analysis. Figure3-2 shows the correlation between the change in industry-level robot exposure in European countries and the United States. The top panel plots the number of industrial robots per thousand workers of 19 industries for the United States and the European countries between 2000 to 2008; the bottom panel displays the variation from 2000 to 2016. In both of these scatter graphs, the vertical axis designates the U.S. robot change and the horizontal robot change in Europe. Industries with increasing robot usage in European countries between 2000 and 2008 integrate more robots in the United States in this time.

A similar relationship is seen to exist between industry-level robot adoption in Europe and in the U.S. between 2000 and 2016. In addition, the automotive industry evidently deploys the most robots in both geographies and this finding provides the indication for the robustness check. This paper calculates both with and without the figures from the automotive industry to ensure the latter does not alone drive any trends.

Figure 3-2: Scatter plot of changes between 2000 to 2008 (top panel) and 2000 to 2016 (bottom panel) in the number of robots per thousand workers for 19 different industries in the U.S. (y-axis) and Europe (x-axis). Both axis are in logarithmic scale. Data sources: International Federation of Robotics (IFR) and KLEMS.



Moreover, this paper calculates the correlation of changes in industry-level robot exposure between the U.S. and EU for two time periods (2000 to 2008 and 2000 to 2016). By observing FigureA3-1 in the appendix, the correlation between the change of industry-level robot exposure in European countries and the United States is 0.973 between 2000 and 2008;

the correlation between the EU and the U.S. robot exposure is 0.963 for the larger interval of 2000 to 2016. These high correlation coefficients prove the relevance of the instrument, EU exposure to robots. This paper also checks the correlation between the instrument and the dependent variables, showing the irrelevance between them. By observing FigureA3-2 in the appendix, the correlation between the EU robot exposure and all dependent variables is negligible. For example, the correlation between EU robot exposure and the total Democrat votes is only 0.0302.
For the first stage relationship between the change in the U.S. exposure to robots and the change in the exposure to robots across the sample of European countries, is expressed by the following formula:

$$\sum_{i\in\mathcal{I}} \ell_{ci,t}\left(\frac{R^{US}_{i,t+4}}{L^{U,S}_{i,t}} - \frac{R^{US}_{i,t}}{L^{US}_{i,t}}\right) = \pi \sum_{i\in\mathcal{I}} \ell_{ci,t}\left(p_{35}\left(\frac{R_{i,t+4}}{L_{i,t}}\right) - p_{35}\left(\frac{R_{i,t}}{L_{i,t}}\right)\right) + \Gamma X_{c,t} + \nu_c \tag{3}$$

where $\Gamma X_{c,t}$ represents a set of control variables and p_{35} indicates the 35th percentile.

3.4 Empirical specification and methodology

This section introduces the regression model that are used in the regression and different methods that are used to estimate models. The aim of this paper is to examine the effect of robot usage on election outcomes in the United States, the general model used in the regression is as follows:

$$Y_{ct} = \beta ROBOTUS_{ct} + \Gamma X_{ct} + \epsilon_{ct} \tag{4}$$

where Y refers to a set of electoral variables. Y comprises the change in total Democrat votes ($DEMO$), the change in weighted Democrat votes ($DEMOPW$), the change in total Republican votes ($REPUB$), the change in weighted Republican votes ($REPUBPW$), the change in the share of Democrat votes to the sum total votes ($SDEMO$), and the change in the share of Republican votes to the sum total votes ($SREPUB$) in the U.S. presidential and congressional elections. X means a set of controls, which includes CONSTRUCT denotes employment of the construction sector, MANUFACT denotes employment of the manufacturing sector, NONTRADE refers to employment of the non-tradable sector, IMPORTCN indicates imports from China to the United States, POP indicates the total population, WORKING denotes the working-age population, BLACK represents the black population, HISPANIC signifies the Hispanics population. In this paper, there are six models used in the estimation; a detailed outline of each model is provided in the appendix.

3.4.1 Two Stages Least Square (2SLS)

Two-Stage least squares (2SLS) estimation is applied to solve the problem of endogenous U.S. robot exposure. Omitted variables and causal relationship are main reasons that cause the endogeneity, in which the U.S. robot exposure may be correlate with the error term. There exists some unobserved effects that may affect the election outcome and they are correlated with the robot exposure. The effect of omitted variables will be captured by the error term, thus the estimated effect of robot exposure may be biased. In addition, election outcomes may, in turn, affect decisions about robot adoption as the different altitude of robots across parties. This causal relationship will cause biased results as well. Therefore, we construct the instrument of U.S. robot exposure by using the robot exposure in eight European countries. The Durbin and Wu-Hausman test is applied to check the endogeneity of U.S. robot exposure. The null hypothesis of this test is that variables are exogenous. Test results reject the null hypothesis, which indicates the 2SLS estimator is more efficient than the OLS estimator. The GMM can also deal with the endogeneity problem, but it is better to use the GMM estimation in the over-identified case, in which the number of instrument is greater than the number of endogenous variable than the 2SLS estimation.

3.4.2 Fixed effects model (FE) and random effects model (RE)

This paper also applies fixed effect estimation and random effect estimation to eliminate the unobserved effects. The main difference between fixed effect model and random effect model is that random effect model assumes those unobserved effects are not correlated with independent variables. In other words, fixed effect model allows the correlation between unobserved effects and independent variables. This paper uses the Huasman test to determine whether fixed effect model or random effect model is better. Test results reject the null hypothesis that random effect model is more efficient. Therefore, we add both time fixed effects and cross-sectional fixed effects in the following estimations.

3.5 Results of the U.S. presidential elections

The aim of this section is to show the main regression results of how robot usage affects election outcome in the United States. Equations 1 and 2 are employed, which use different estimation methods. As mentioned, the first one is the ordinary least square estimation (OLS) and the second the fixed effect estimation (FE); the third is the random effect estimation (RE) and the fourth and final one the two-stage least square estimation (2SLS).

3.5.1 Analysis of the effect of changes in robot exposure between 2000 and 2016 on changes in the U.S. presidential election outcomes

Findings from the U.S. presidential election by using whole period cross-section data

1 The regression result under OLS estimation shows that robot exposure has a positive and significant effect on the weighted Democrat total votes. For each additional robot, there is a 19.75 vote increase for the Democrats. In addition, the effect of robot exposure on the weighted total Republican votes is also positive and significant. Each extra robot yields a 8.81 vote rise for the Republicans;

2 By using the IV estimation, U.S. robot exposure affects the total Democrat votes in presidential elections negatively and significantly at a 1 percent significance level. Robot usage has a positive and significant effect on the total Republican votes in presidential elections from 2000 and 2016.

This paper begins its enquiry into robot usage and election outcomes in the United States by using cross-sectional data of the whole sample period (2000 to 2016). The change in robot exposure from 2000 to 2016 in the eight European countries becomes the instrument of robot exposure change in the United States across this same span. This instrument process imitates the identification strategy of Acemoglu and Restrepo (2017), who use exogenous EU robot exposure from 1993 to 2007 as the proxy of U.S. robot exposure.
The dependent variable includes the unweighted and weighted total votes of Democrats and Republicans (DEMO, DEMOPW, REPUB and REPUBPW). The independent variable is robot exposure and all control variables are listed in Table3-1. The regression results are estimated using different methods, such as OLS and IV. This part only displays the result for the main independent variable, which is the effect of U.S. robot exposure on election outcome and the full regression results are shown in TableA3-1 and TableA3-2 in the appendix. Panel A in Table3-2 displays the OLS regression result. For each additional robot, there is a 19.75 vote increase for the Democrats and this positive effect is significant at a 10 percent significance level. Robot exposure also has a strong, positive correlation with the weighted total Republican votes, with each extra robot leading to a 8.81 vote rise. Panel B displays the estimation result by adding the instrument. The Democratic party loses 7335979.8 total votes in the U.S. presidential elections between 2000 and 2016 for every one robots added; this effect is significant at a 1 percent significance level. On more robots are worth 1973992.3 more total votes for the Republicans, and this impact is significant at a 10 percent significance level.

Table 3-2. Cross-sectional estimates of the change in exposure to robots on US presidential outcomes from 2000 to 2016

	ESTIMATES for 2000 to 2016			
	DEMO	DEMOPW	REPUB	REPUBPW
	Panel A. OLS estimation			
Change in exposure to robots from 2000 to 2016	-998107.8	19.75*	854087.3	8.81*
	(-1.65)	(2.45)	(1.55)	(2.37)
Observations	739	739	739	739
	Panel B. IV estimation			
Change in exposure to robots from 2000 to 2016	-7335979.8***	-22.83	1973992.3*	-7.27
	(-7.14)	(-1.63)	-2.09	(-1.13)
Obsevations	686	686	686	686
Control variables	✓	✓	✓	✓

Notes: The table presents OLS and IV estimates of the change in exposure to robots on US presidential election outcomes. Each sub-panel presents results under different estimation methods. Each column presents different specification of the dependent variable (unweighted and weighted total votes for democrats and republican in the US presidential election). The models are estimated in the commuting zone level and the weighted total votes of different parties are weighted by 2000 commuting zone population. The coefficients with *** are significant at the 0.1 percent confidence level; with ** are significant at the 1 percent confidence level; and with * are significant at the 5 percent confidence level.

This analysis follows the same procedure as Acemoglu and Restrepo (2017), who compare the difference in votes in two periods (2000 and 2016). Conspicuously, robot exposure has the opposite effect on the total votes of Democrats and Republicans in the U.S. presidential elections between 2000 and 2016. Those in fear of their jobs and income in response to the rise of robotics may turn to the Democratic Party, who are perceptibly more willing to redistribute wealth to protect the middle and lower classes. Ergo, the expansion of robots could be expected to swell the Democratic vote and even dissuade those at the polls from choosing Republican. However, Donald Trump, the Republican candidate for the 2016 U.S. presidential election, promised to revitalise manufacturing and thereby employment in the country. In respect of this campaign promise, the increase in robots might even have boosted Republican support. Voting likely depends more on the candidate than the party.

Though this study determines a link between robot growth and total Republican vote increase between 2000 and 2016, the robustness of this finding requires further inspection. No specific trends are found between the total votes for each party and macroeconomic indicators of this time. Another robustness check of the changes between 2000 and 2016 is conducted by investigating an additional two sub-periods (2000 to 2012 and 2000 to 2008). These regression results, compared with those for the whole period, imply a different effect of robot exposure on election indicators. In other words, the previous finding is not robust. For the general effect of robot exposure on total votes, the panel study provides further insight. Duly, the remainder of this paper is devoted to panel studies and cross-sectional analysis of the sub-periods, to ascertain the impact of robot exposure on presidential votes under different data settings. The different electoral ramifications of robot usage for Republicans and Democrats will also be elucidated. It will be considered, for instance, whether the party or specifically party policy shapes the robots' impact.

3.5.2 Panel analysis of the U.S. presidential elections

Findings from the U.S. presidential election by using panel data

1 Under the OLS estimation, the U.S. robot exposure has negative and significant effect on weighted Democratic votes, total Democratic votes and total Republican votes between 2000 and 2016;

2 Under the 2SLS estimation, the increase in every new robot is met with a 58.01 weighted vote decline for the Democrats between 2000 and 2016; EU robot exposure between 2000 and 2016 is employed as the instrument

3 For the IV regression with fixed effects and leads of robots, U.S. robot exposure has a negative and significant effect on the total Democratic votes and total Republican votes between 2000 and 2016.

Baseline results of OLS

TableA3-3 (see appendix) presents results of both the change in total Democratic and total Republican votes by using the OLS estimation. Judging by TableA3-3' s pane 1, robot usage has a negative and significant effect on the weighted total votes of the Democratic Party ($DEMOPW$) , with each extra robot causing a 59.21 vote loss. This negative correlation is significant at a 1 percent significance level. Turning to the Republicans, panel 2 illustrates that exposure to robots negatively affects weighted total Republican votes ($REPUBPW$), though the correlation is insignificant even at a 10 percent significance level. In terms of total Democratic and total Republican votes, which are shown in panel 5 and panel 6, robot usage has negative and significant effect on both votes at 1 percent significance level.
In addition, this paper estimates the relationship between robot usage and changes in both Democrat ($SDEMO$) and Republican ($SREPUB$) share of the cumulative total. It first calculates total votes and then share of votes. As shown in panel 3 of TableA3-3, exposure to robots in the United States negatively and significantly impacts the Democrat share of votes. Panel 4 suggests the positive effect of robot exposure on the Republican share of votes, and this is significant at a 1 percent significance level. However, the OLS estimation result may be biased due to the possible endogeneity. We can see the model with total Democrats votes has the highest adjusted R-squared, which means this model has the highest explanatory power.

Results of FE an RE estimation

Then, this paper applies fixed effect and random effect models to regress robot exposure and election outcome.
Before the FE estimation, it assesses the heterogeneity to analyze whether the fixed effect is required. For the model that uses DEMOPW as the dependent variable, FigureA3-3, in the appendix, shows the chronological heterogeneity analysis. The red plots are the yearly mean of total Democrat votes, which is largely steady. After the visual pre-analysis, dummies are added to the regression for each year and a fixed effect significance test is conducted. The p-value of 0 indicates the existence of a time fixed effect.
Panel 1 of TableA3-4 depicts the FE estimation results, which encompass both commuting zone and time fixed effects, in regard to changes in the weighted total Democratic votes; one new robot leads to a fall of 44.06 votes. The correlation between robot usage and weighted total Democrat votes is still negative and significant at a 5 percent significance level. Turning to vote share, Panel 4 once again exhibits the significant and negative effect of robot exposure on Democrat electoral performance. As for the Republican share of votes, robot penetration affects it negatively and significantly at 5 percent significance level.
Furthermore, it is interesting to investigate the effect of future robot usage on the current election outcomes. This paper then adds the leads of robots exposure into the model with the fixed effect estimation. Panel 2 in TableA3-4 shows the FE estimation result of DEMOPW with four years leads of robots exposure, the leads of robot exposure has opposite effect compared with the current robot exposure on the total votes of the democratic party. According to panel 2 in TableA3-4, the current robot usage has positive and significant influence on democrat's weighted total votes, while future robot exposure has negative and significant effect on the total votes of democratic party. However, the FE estimation result of DEMOPW without robots leads shows the negative effect of current robot exposure in panel 1 of TableA3-4. This finding indicates the importance of future robot usage on today's election outcomes, people's voting behavior may be affected by future robot exposure.
In addition to the fixed effect estimation, this paper regresses models by using the random effect estimation. Panel 1 of TableA3-5 in the appendix shows one more new robot used is correlated with 59.21 decreasing votes of democratic party under the RE estimation and this negative correlation is significant at 1 percent significance level. As for the RE regression result at share level, the exposure of robots has negative and significant influences on the share of democrat's votes to the sum of democrat's votes and republican's vote by observing panel 2 of TableA3-5. In accordance with the FE estimation result, the increasing use of industrial robots is associated with the increasing share of republican's votes to the sum of democrat's votes and republican's votes under the RE estimation. Based on the RE regression result in panel 4 of TableA3-5, the positive relationship between robot usage and the share of republican's votes is significant at 1 percent significance level.

After conducting both FE and RE estimation, this paper compares the fixed effect model and random effect model in the next step. The selection between fixed effect model and random effect model is determined by whether the unobserved individual effect is associated with regressors. The data set in this paper contains relatively short time periods and large cross section units, if the individual cross-sectional effect is random, the random effect estimation will be more efficient than the fixed effect estimation. Then, this paper conducts the hausman test to selecting between the fixed effect model and the random effect model. TableA3-6 in the appendix presents the result of the hausman test for the model that uses DEMOPW as the dependent variable, the null hypothesis that the RE estimator is the same as the FE estimator is rejected as the p-value is equal to 0. Therefore, the RE model will not provide more efficient estimation results than the FE model.

Baseline results of 2SLS

As pointed in the previous section, the problem of endogeneity leads to the use of 2SLS estimation. This paper uses the 35th percentile robot exposure of eight European countries as the instrument of the robot exposure of the United States. The paper has proved the validity of the instrument in the previous section and this section presents the regression result of main models by using 2SLS estimation.

In the first stage, this paper regress the U.S. robots exposure (ROBOTUS) with the EU robots exposure (ROBOTEU) and all other independent variables. TableA3-7 in the appendix, indicates the first stage regression result between the instrument and U.S. robot exposure; U.S. robot exposure is significantly correlated with this instrument, as the p-value is equal to zero. Each additional robot deployed in the United States is associated with a 0.163 unit increase in EU robots . For the second stage, the DEMOPW model is first run, followed by DEMO, REPUBPW and REPUB. Panel 1 of appended TableA3-8 presents the second stage regression result of DEMOPW; U.S. robots exposure still has a negative and significant effect on total Democratic votes, at a 1 percent significance level. According to panel 2, U.S. robot exposure affects total Democrat votes votes negatively and significantly by using the instrument variable. As for the weighted total votes of Republican, robot exposure influences it negatively and significantly, as panel 3 evidences. Total votes of Republican is affected by robot exposure positively and significantly based on panel 4.

As previously discussed, a fixed effect model is better than a random effect model, hence the use of IV estimation with fixed effects. The results of the IV regression, which employs the time fixed effects of different specifications of the dependent variable, are shown in Panel A of Table3-3. Exposure to robots in the United States has a negative and significant effect on the total votes of Democrats and Republicans at a 1 percent significance level. Moreover, each additional robot is accompanied by a loss of 70.66 weighted total votes for the Republicans, an effect which is significant at a 1 percent significance level. Furthermore, this paper double checks the endogeneity by adding the four-year leads of U.S. robots to the regression. As

discussed before, the future robot exposure may affect the current election outcomes. In panel B of Table3-3, the four-years leads of U.S. robot exposure is seen as endogenous and the instrument is the four-years leads of EU robot exposure. The U.S. robot exposure still affect the total votes of Democrats and Republicans negatively and significantly at 5 percent and 1 percent significance level respectively. Moreover, each additional robot is accompanied by a loss of 53.85 weighted total votes for the Republicans, an effect which is significant at a 5 percent significance level. In addition, we can see the within R-squared for the model with total Democratic votes and total Republican votes are higher than weighted votes models, which indicates higher explanatory power of unweighted models.
In conclusion, the panel analysis, which expands the range of observation, detects the same negative and significant impact effect of robot exposure on total votes of Democrats and Republicans. For these negative effect of robots on Democrats and Republican, this may caused by political polarization. The increasing polarization disappoint people and they may think this situation will not get better and less people to vote. They don't believe the government can solve social difficulties, thus decline in political engagement. In section 3.5.1 that analyse the effect of changes in robot exposure between 2000 and 2016 on the changes of voting outcomes between 2000 and 2016, robot exposure shows contrasting effect on total votes of Democrats and total votes of Republican.

Table 3-3. Panel estimates of the change in exposure to robots on US presidential outcomes from 2000 to 2016

	PANEL ESTIMATES from 2000 to 2016			
	DEMO	DEMOPW	REPUB	REPUBPW
	Panel A. IV with fixed effect			
Change in exposure to robots	-1.27e+08***	10.75	-9.71e+07***	-70.66***
	(-13.05)	(0.48)	(-10.94)	(-3.53)
Observations	2767	2767	2767	2767
	Panel B. IV with fixed effect and leads of robots			
Change in exposure to robots	-19708.13*	124.7***	-150039.14***	-53.85*
	(-2.53)	(5.00)	(-17.15)	(-2.16)
Observations	2074	2074	2074	2074
Control variables	✓	✓	✓	✓

Notes: The table presents IV estimates of the change in exposure to robots on US presidential election outcomes with fixed effect and U.S. robot leads. Each sub-panel presents results under different estimation methods. Each column presents different specification of the dependent variable (unweighted and weighted total votes for democrats and republican in the U.S. presidential election). The models are estimated in the commuting zone level and the weighted total votes of different parties are weighted by 2000 commuting zone population. The coefficients with *** are significant at the 0.1 percent confidence level; with ** are significant at the 1 percent confidence level; and with * are significant at the 5 percent confidence level.

3.6 Panel analysis of the U.S. Congressional election

Having examined the effect of robot exposure on presidential elections , this paper assesses the influence of robot penetration on congressional election outcomes. The data for U.S. congressional elections is sourced from the MIT election lab; the data for the other variables is the same as for the U.S. presidential elections. Likewise, congressional elections between 2000 and 2016 are considered. Congressional elections elect representatives for each congressional district, of which there are 435 across the 50 states of America. Therefore, the final regression data for this congressional election part are aggregated at the congressional district level and not at the commuting zone level, as for the presidential elections.

Findings from the U.S. congressional election

1 The robot exposure affects the unweighted total votes of the republican party in the U.S. congressional election positively and significantly under different estimation methods from 2000 to 2016.

For its dependent variables, this paper uses the change in total Democratic ($DEMO$) and total Republican ($REPUB$) votes, the change in weighted Democrat ($DEMOPW$) and weighted Republican ($REPUBPW$) votes, and the change in the Democrat ($SDEMO$) and Republican ($SREPUB$) share of the total Republican and Democrat votes in United States congressional elections between 2000 and 2016. Robot exposure ($ROBOTUS$) remains the independent variable. The control variables are the same as for the presidential regressions but aggregated at the congressional district level.

Turning to the regression process, this paper runs the pooled model, the fixed effect model, the IV model, and the IV model with fixed effect for a series of dependent variables. Firstly, Panel A of TableA3-11 shows the regression result for DEMO, REPUB, DEMOPW, REPUBPW, SDEMO, and SREPUB by using the OLS estimation. According to TableA3-11 in the appendix, robot exposure has a significant effect only on the change of Republican votes (REPUB). The increasing use of robots boosts the total Republican votes in U.S. congressional elections. Otherwise, the pooled model finds only insignificant impacts. Secondly, the fixed effect regression results for DEMO, REPUB, DEMOPW, REPUBPW, SDEMO, and SREPUB are displayed in panel B of TableA3-11. Robot penetration once again has a positive effect on total Republican votes, but no significant effect is detected for all dependent variables.

The instrument strategy is the same in the congressional study as in the presidential study, whereby robot exposure in eight European countries is the instrument for the robot exposure in the United States at the congressional district level.

Panel C of TableA3-11 exhibits the IV regression results of DEMO, REPUB, DEMOPW, REPUBPW, SDEMO, and SREPUB. As with the previous OLS estimation results, the increase in robot exposure still has a positive and significant influence on Republican votes and the share of Republican but no significant impact on the remaining dependent variables. Finally, this paper runs the congressional regression by using the IV model with fixed effect. The regression results for DEMO, REPUB, DEMOPW, REPUBPW, SDEMO, and SREPUB are shown in TableA3-11. It is noticeable that the regression result is similar to the previous result, the exposure of robots affect the total votes of the republican party positively, but insignificantly. For the remaining panels, the robot exposure still has no significant effect on electoral independent variables.

Based on these regression results by different regressing methods, it is interesting that the robot exposure only affect the total votes of the republican party in the U.S. congressional election. When the dependent variable changes to the weighted total votes of the republican party, the effect of robot usage become insignificant. The total votes for one party by an congressional district with relatively larger population and the total votes for the same party by another congressional district with relatively smaller population will be different in absolute values. If the total votes are not weighted by the population, congressional district with larger population will have larger effect and the regression result may be overrated. The aim of weighting total votes is to make the effect in each congressional district is the same in size relatively. Though the significant and positive effect of robot exposure on total votes of the republican party may be overrated, this finding still provides evidence that the robot usage may affect the republican party's voting outcomes in congressional elections.

Furthermore, the congressional regression results indicate the robot usage indeed affect how people vote in the U.S. election, but it does not affect the voting behavior only in one direction. The direction may depends on the person who leads the party. For example, supposing the candidate of the democratic party declares some statements about employment protection, voters will be more willing to support the democratic party. Therefore, the candidate is very important in deciding the direction of robot's effect on the voting behavior.

This paper regresses the robots exposure on the presidential election data in the United States at commuting zones level firstly and finds the significant correlation between U.S. robot usage and a set of electoral dependent variables, such as total votes of the democratic party. Then, this paper runs regressions between exposure of robots and the same set of electoral variables by using the U.S. congressional election data at congressional district level. The congressional study aims at providing more evidence to support the finding that the significant effect of robot exposure on election outcomes from the presidential study. In the congressional study, this paper also finds the significant relationship between robot exposure and voting outcomes of the republican party, though the result may be overrated. In conclusion, both the presidential level study and congressional level study provide evidence to prove that the robot exposure will affect the voting outcomes in the Unites States. As discussed in the literature, the increasing usage of robots affects the employment and income of people, the changes in the general economic condition may leads to changes in the political side, such as the voting outcomes. Furthermore, the empirical study in this paper provides evidence to support the possible link between robots usage and political outcomes from the theoretical side.

3.7 Cross-sectional analysis of sub-periods

Previous empirical studies use panel data to perform regression analysis. This section runs the regression using cross-sectional data for each election period, detecting changes between two election year. For example, it can be seen whether the effect of robot usage on voting outcomes for one party changes from positive to negative or insignificant to significant between years. Four regressions are run, for the years 2000, 2004, 2008, and 2012 respectively, revealing any changes.

It is also tested whether or not the impact of robot exposure varies across the United States. The distribution of industrial robots is likely uneven across cities and states; some areas will have higher robot penetration than others. According to the industrial robot data provided by the International Federation of Robots (IFR), the disparities in the numbers of industrial robots across states are not inconsiderable. Therefore, this paper conducts regressions for areas with a large stock of industrial robots to examine the link between robot exposure and voting behaviour, given that the effect of robots will be more distinguishable in these areas than in those with a small stock of robots.

Six states with a relatively large stock of industrial robots are selected. The first is Michigan, home to many of the big players in the automotive industry, such as General Motors and Ford. These company factories have a high demand for industrial robots and this is one of the main reasons why Michigan alone accounts for nearly 12 percent of the total robot stock in the United States (Mark, 2017). The second and third states are Ohio and Indiana, which constitute 8.7 and 8.3 percent respectively of the total U.S. robot stock, according to Brookings analysis of data from the International Federation of Robotics (Mark, 2017). The final three states are Illinois, California, and New York City. The data for each state is separated by FIPS code. Then, regressions between robot exposure and voting outcomes are run on each of the six selected states. The process of regression is divided into four steps by using four different dependent variables. The dependent variables, which are total Democrat ($DEMO$) and Republican ($REPUB$) votes, the weighted total Democrat ($DEMOPW$) and weighted total Republican ($REPUBPW$) votes, use the 2000 to 2016 presidential election data.

For the presidential election, TableA3-12 in the appendix presents the cross-sectional regression results for robots exposure and the total votes for the Democratic Party ($DEMO$)). Each column in this table denotes a different time period and each row represents one of the aforementioned states . The figures in this table only include the sign and significance of robot exposure on the electoral dependent variable and the tables to follow in this section are the same. It is apparent from this table that robot exposure has a negative and almost significant effect on DEMO for five states in every election cycle. The sign of robot exposure does not change over time, suggesting that Democratic candidates may not have too much input on their employment policy, changes to which can be used in presidential elections to gain more votes against the backdrop of rising robotics. Notable is Ohio state, where robot exposure has a positive influence on DEMO in 2004 and 2008, though this effect is insignificant.

TableA3-13 contains the cross-sectional regression results for the effect of robot exposure on total Republican votes in the U.S. presidential elections ($REPUB$). Columns 3 and 4 show that the sign of robots exposure's impact on total Republican votes changes from negative to positive in two election periods for nearly all states. In the 2008 to 2012 election period , robot usage has a negative influence on Republican voting outcomes, before this effect becomes positive between 2012 and 2016. This implies that the Republican candidate's claims he will protect employment may have been understood as keeping the rise of robots in check. This inference is based on the assumption that most voters regard robots as threatening to their employment and income and, as such, will favour the party promising to protect jobs, which the presidential choice in 2016 seems to support. The victory of the Republican candidate, Donald Trump, is consistent with the findings in TableA3-13 , where the positive effect of robots on Republican total votes is highlighted. The regression in the first row uses the whole dataset across different election periods, not the selected state data The results show the sign changes in the latter two election periods . Of the seven regression results in TableA3-13, New York is the only one without the sign change, thus this will not affect previous analysis.

TableA3-14 includes the cross-sectional regression outcomes of how robot usage affects the weighted total Democrat votes ($DEMOPW$) in the U.S. presidential election. Unmistakably, all state results, including those using the whole dataset, show the same sign for every election periods. From 2000 to 2004, robot exposure affects the weighted Democrat votes negatively and significantly; at this point, the robot effect becomes positive between 2004 and 2008. Barack Obama, the Democratic candidate, subsequently wins the 2008 U.S. presidential election. This election result supports the revelation about the sign changes in the first two election periods. Turning to the latter two election periods, robot exposure impacts the total Democrat votes negatively and significantly for all seven regressions. It is important that the democratic party lose the 2016 presidential election in the United States, suggesting the candidate of democrats may not pay attention to decrease the unemployment rate and protect people's benefit on this aspect. This inference is also based on the previous hypothesis that the majority of people believe the increasing penetration of robots brings threats to their jobs and they will support the party with negative actions on robot development. As the increasing usage of industrial robots in the latter two election periods, the democratic party receives negative effect from that and this negative effect is reflected in the final election outcomes.

Turning to the final table of the first part of cross-sectional analysis, TableA3-15 presents the regression result of the robot usage's effect on the weighted total votes of the republican party in the U.S. presidential election. The result is very similar to the result without weights of the republican party. All six states and the one with the whole data have the same sign of robots' effect on voting results in every election periods. In the election cycle from 2008 to 2012, the robot exposure affects the weighted republican's votes negatively, but this effect changes to positive effect from 2012 to 2016. As discussed in the regression result of REPUB, the sign of robots' effect also changes from negative to positive in the latter two election periods. The result in TableA3-15 provides evidence to support the analysis in REPUB regression. The republican party wins the 2016 presidential election in the United States and the increasing robots usage has positive impact on republican's votes. The possible explanation could be that the candidate of the republican party shows negative altitude on robots usage as he demonstrates employment protection in the campaign declaration. This explanation is based on the assumption that the great majority of voters consider the negative effect of robots is greater than the positive effect on their life, thus they will vote the party with limitations on the use of robots.

Another finding by comparing TableA3-14 and TableA3-15 is that the sign of robot's effect on DEMOPW and REPUBPW is the same in the first three election period. For example, the robot exposure affect the weighted total votes of the democratic party and the republican party positively and significantly from 2004 to 2008. The first possible explanation of this finding could be that both the participation rate for voting the democratic party and the republican party increases within 2004 to 2008. The second possible reason is some independent candidates become democrats or republicans.

3.8 Robustness Check

This part aims to check the robustness of election results by applying different specification of robots exposure and different controls. For briefness, this check will pay attention on the pooled model and the reduced-form model of weighted total votes of the democratic party in the U.S. presidential election ($DEMO$).

According to Figure3-2, the automotive industry has the highest robot exposure from 2000 to 2016 compared with other industries. TableA3-16 displays the DEMO regression results;

different specification and control variables are employed to demonstrate that previous calculations are not skewed by the automotive industry. Panel A is the baseline-specification regression result for total votes of the Democratic Party in the presidential election. Panel B uses a different specification of robot exposure, which excludes robot data from the automotive industry. Panel C applies a different control variable by adding robot exposure in the automotive industry. Column 1 presents the result of DEMO with the pooled model and column 2 presents the result if DEMO with the IV model, which has European robot exposure as the instrument.

Panel B, even without the automotive industry, deems the effect of robot exposure on the total votes of Democrats to be negative and significant at a 1 percent significance level. Though panel B uses less varied robot data, the effect of robots on Democrat's total votes is still negative and significant. Turning to the IV regression in panel B, robot exposure affects Democrat's total votes negatively and significantly. Increasing robots usage leads to decreasing total votes of Democrats. The value of this coefficient is smaller than the coefficient in column 2 of panel 1 (-1.97e+08), which does not exclude the automotive industry's robot exposure.

In terms of panel C, which adds automotive-industry robot exposure as one of its controls, robot exposure still has a negative and significant effect on total votes of Democrats. Though the absolute value of the coefficient (-1.11e+08) is smaller than the that in column 1 of panel A (-1.18e+08), it is still significant at a 1 percent significance level. As the IV regression conveys, increase in robots exposure has negative and significant impacts on total Democrat votes. This result corresponds with that in column 2 of panel A and is significant at a 1 percent significance level.

Though using a different specification and control variable, the effect of robot exposure is still negative and significant on total Democrat votes in the U.S. presidential election. This attests to the robustness of the previous baseline results.

Further robustness checks of the effect of robot exposure on total Republican votes in U.S. congressional elections are also in keeping with the baseline regression results for these same elections. TableA3-17 sets out this robustness check, which employs the same strategy as the previous control of the presidential elections. As panel B demonstrates, robot exposure is still significant on REPUB when the automotive industry data is omitted. In terms of panel C, robot exposure in the automotive industry is added as a control variable and still affects REPUB significantly. This proves that the previous congressional regressions are robust.

3.9 Conclusion and Discussion

The bounding advance of new technologies in recent times, to which industrial robots certainly belong, has engendered an anxiousness amongst workers that their labour and livelihood will fall victim to automation. The transformative effect of new technology on the general economic conditions, such as employment and income, has been covered by many academics. However, critical attention to the impact of new technology, especially robots, on the political economy, for instance, election results, is, at best, negligible. As the threat of technical innovation to the labour market becomes more grave, voters are increasingly sensitive to employment policies .

Indeed, new technologies have concomitant social costs, as some workers experience decreasing income or unemployment, causing social unrest which may even jeopardise the incumbent political party. Modernity, thus, is not the sole offspring of such rapid technological development; they also beget revolutionary political ideals. Within this context, the candidate of a party who pledges to protect human labour is likely to attract support, an indirect consequence of new technology on voter preference. The United States, as the country with the highest industrial robot stock in the world, is chosen as the object of research.

Identifying the effect of industrial robots on election outcomes in the United States between 2000 and 2016 is the goal of this study. It tries to find the exogenous exposure to robots in the United States by using robot exposure in eight European countries. This strategy ensures that industry-level robot exposure is not skewed by endogenous trends in other industries. The empirical work begins with cross-sectional analysis of the whole period, which reveals that robot exposure has the opposite effect on total votes for the Republicans and Democrats in presidential elections. It is important to establish the exact effect of robot exposure on election outcomes in this period and discern the driving force behind it. Therefore, this paper carries out a panel investigation of the U.S. presidential elections at the commuting zone level, followed by a panel estimation of the U.S. congressional elections at a congressional district level and then a final, cross-sectional analysis of the presidential elections. Based on these estimations, this paper notes: (1) In U.S. presidential elections, the impact of increased robot exposure is significantly reflected by the decreasing votes of Democrats between 2000 and 2016; (2) Rises in the industrial robot density affect the total votes of the Republican party positively and significantly in the U.S. congressional election between 2000 and 2016. Hudson (2019) finds young people seems to be more support the adoption and application of robots than older people. In other words, older people are more afraid of robots than young people. At the same time, older people prefer the republican than democrats. This mechanism provides possible explanation for the positive effect of robots on the republican. Several robustness checks corroborate these findings. In addition, this paper, based on the cross-sectional analysis, demonstrates that robot exposure negatively affects the total Democrat votes and positively affects total Republican votes in the 2016 presidential election. Together, these findings indicate that increasing robot usage shapes voting behavior and, ergo, election outcomes in the United States. Moreover, this influence is not one-directional, which means that robot exposure has a different effect on the election results of the same party in different sub-periods. Hence, party is not the determinant of robots' electoral sway. If it were, robot usage would be consistent in its effect. Either policy, or the representing candidate, steers the electoral effect of robots. If the party provides signal that they will protect the employment under the threaten from robots, that party may receive more supports.

In conclusion, this paper investigates the relationship between robot usage and election outcomes for the first time, providing a valuable foundation on which to build future research. For example, if data on other new technologies can be accessed, its electoral upshot can be compared with that of robots. It might be discerned whether and how different technologies affect different societal strata. Similarly, future scholars could juxtapose the political impact of robots in other countries with the United States.

3.10 Appendix

In this section of the appendix, we are going to displaying tables of regression results between U.S. robot exposure and different electoral variables under different estimation methods and results of diagnostic tests.

The first table presents OLS estimates of the change in exposure to robots on US presidential election outcomes by using the cross-sectional data from 2000 to 2016. Each column presents different specification of the dependent variable (weighted total votes for democrats; weighted total votes of republican; the share of democrats' votes; and the share of republican's votes in the US presidential election).

Table A3-1: Whole cross-sectional estimates of the change in exposure to robots on US presidential outcomes from 2000 to 2016 under OLS.

	OLS estimates for the changes between 2000 and 2016			
	DEMO	REPUB	DEMOPW	REPUBPW
U.S. robot exposure	-998107.8 (-1.65)	854087.3 (1.55)	19.75* (2.45)	8.811* (2.37)
Total population	-0.00404 (-1.77)	0.00113 (0.54)	-0.000000187*** (-6.16)	-8.73e-08*** (-6.22)
Working age population	0.0711*** (4.53)	0.0194 (1.35)	-0.000000726*** (-3.47)	-0.000000199* (-2.05)
Black population	0.0321 (1.64)	-0.0699*** (-3.91)	0.00000144*** (5.51)	0.000000444*** (3.69)
Hispanics population	0.126*** (7.03)	-0.0142 (-0.86)	0.000000218 (0.91)	1.39e-08 (0.13)
Share of adults with less than a high school diploma	-272.0 (-1.11)	128.2 (0.57)	0.0000182 (0.01)	0.000420 (0.28)
Share of adults with a high school diploma	-569.4 (-1.73)	43.4 (0.14)	-0.00241 (-0.55)	-0.0000507 (-0.02)
Share of adults with a bachelor's degree or higher	222.9 (0.51)	-663.1 (-1.67)	0.00483 (0.83)	-0.00122 (-0.46)
Employment of construction industry	2.837*** (11.01)	0.272 (1.15)	0.00000905** (2.63)	0.00000296 (1.87)
Employment of manufacturing industry	-0.452*** (-5.23)	-0.537*** (-6.78)	-0.00000386*** (-3.34)	-0.00000200*** (-3.75)
Employment of non-tradable industry	-0.498* (-2.52)	0.731*** (4.04)	0.00000684** (2.59)	0.00000284* (2.33)
Share of employment in routine jobs	-8024.0*** (-4.03)	5617.8** (3.09)	0.0533* (2.01)	0.0340** (2.78)
Imports from China to the U.S.	451.5*** (5.00)	195.7* (2.37)	0.000300 (0.25)	0.000468 (0.84)
Observations	739	739	739	739
Adjusted R-squared	0.8135	0.4402	0.3457	0.2008

Notes: The models are estimated in the commuting zone level and the weighted total votes of different parties are weighted by the commuting zone population. The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).

The second table presents IV estimates of the change in exposure to robots on U.S. presidential election outcomes by using the cross-sectional data from 2000 to 2016. The US robot exposure is instrumented by the EU robot exposure from 2000 to 2016. Each column presents different specification of the dependent variable (weighted total votes for democrats; weighted total votes of republican; the share of democrats' votes; and the share of republican's votes in the U.S. presidential election).

Table A3-2: Whole cross-sectional estimates of the change in exposure to robots on US presidential outcomes from 2000 to 2016 under IV regression.

	IV estimates for the changes between 2000 and 2016			
	DEMO	REPUB	DEMOPW	REPUBPW
U.S. robot exposure	-7335979.8***	1973992.3*	-22.83	-7.267
	(-7.14)	(2.09)	(-1.63)	(-1.13)
Total population	-0.00694**	0.00176	0.000000219***	-0.000000100***
	(-2.81)	(0.77)	(-6.52)	(-6.50)
Working age population	0.0871***	0.0179	-0.000000605**	-0.000000145
	(5.33)	(1.19)	(-2.71)	(-1.42)
Black population	0.0940***	-0.0832***	0.00000184***	0.000000588***
	(4.33)	(-4.16)	(6.20)	(4.33)
Hispanics population	0.0980***	-0.0127	7.92e-08	-4.14e-08
	(5.19)	(-0.73)	(0.31)	(-0.35)
Share of adults with less than a high school diploma	-478.0	157.5	-0.00131	-0.000121
	(-1.83)	(0.65)	(-0.37)	(-0.07)
Share of adults with a high school diploma	-639.2	143.0	-0.00392	-0.000205
	(-1.79)	(0.43)	(-0.80)	(-0.09)
Share of adults with a bachelor's degree or higher	31.78	-643.4	0.00342	-0.00193
	(0.07)	(-1.52)	(0.55)	(-0.67)
Employment of construction industry	2.174***	0.333	0.00000514	0.00000149
	(7.82)	(1.30)	(1.36)	(0.86)
Employment of manufacturing industry	0.146	-0.633***	-0.000000275	-0.000000630
	(1.23)	(-5.80)	(-0.17)	(-0.85)
Employment of non-tradable industry	-0.431*	0.744***	0.00000725**	0.00000295*
	(-2.10)	(3.94)	(2.59)	(2.30)
Share of employment in routine jobs	-9818.6***	6154.0**	0.0409	0.0283*
	(-4.68)	(3.19)	(1.43)	(2.16)
Imports from China to the U.S.	315.2***	202.6*	-0.000464	0.000124
	(3.31)	(2.31)	(-0.36)	(0.21)
Observations	686	686	686	686
Within R-squared	0.8096	0.4361	0.3456	0.1989

Notes: The models are estimated in the commuting zone level and the weighted total votes of different parties are weighted by the commuting zone population. The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).

The third table presents OLS estimates of the change in exposure to robots on US presidential election outcomes by using the panel data from 2000 to 2016. Each column presents different specification of the dependent variable (weighted total votes for democrats; weighted total votes of republican; the share of democrats' votes; and the share of republican's votes in the U.S. presidential election).

Table A3-3: Panel estimates of the change in exposure to robots on US presidential outcomes from 2000 to 2016 under OLS.

	OLS estimates for the effect of robot exposure on U.S. presidential election outcomes by using panel data from 2000 to 2016					
	DEMOPW	REPUBPW	SDEMO	SREPUB	DEMO	REPUB
U.S. robot exposure	-59.21***	-1.167	-55.64**	55.64**	-118479278.3***	-22658442.5***
	(-4.47)	(-0.09)	(-3.01)	(3.01)	(-19.18)	(-3.92)
Total population	-0.0198***	-0.0161***	0.00270	-0.00270	-1310.0	-682.4
	(-10.98)	(-9.28)	(1.58)	(-1.58)	(-1.72)	(-0.96)
Working age population	0.0546***	-0.0143	-0.0259*	0.0259*	28152.6***	6424.0
	(4.61)	(-1.25)	(-1.97)	(1.97)	(4.97)	(1.21)
Black population	0.0495**	0.00691	0.0418**	-0.0418**	8422.1	-11152.1
	(3.26)	(0.47)	(2.59)	(_2.59)	(1.19)	(-1.68)
Hispanics population	-0.0402***	0.0327**	0.0164*	-0.0164*	-13985.2***	-24520.1***
	(-3.77)	(3.17)	(2.20)	(-2-20)	(-4.10)	(-7.67)
Share of adults with less than a high school diploma	-0.00295	0.0671**	-0.0994***	0.0994***	-13134.6	3327.4
	(-0.14)	(3.26)	(-3.99)	(3.99)	(-1.25)	(0.34)
Share of adults with a high school diploma	-0.0565	-0.0528	-0.161***	0.161***	-12584.7	-44888.5***
	(-1.94)	(-1.88)	(-4.87)	(4.87)	(-0.88)	(-3.35)
Share of adults with a bachelor's degree or higher	0.0551	-0.0333	0.000441	-0.000441	-3805.8	-48087.4**
	(1.60)	(-1.00)	(0.01)	(-0.01)	(-0.22)	(-3.02)
Employment of construction industry	2.036***	0.803***	0.319	-0.319	1728926.0***	658088.2***
	(10.81)	(4.41)	(1.53)	(-1.53)	(19.62)	(7.98)
Employment of manufacturing industry	0.0700	0.242**	0.335***	-0.335***	630667.2***	155105.2***
	(0.78)	(2.79)	(3.42)	(-3.42)	(15.63)	(4.11)
Employment of non-tradable industry	-0.944***	-0.0749	-0.114	0.114	-854780.1***	-99515.6
	(-6.04)	(-0.50)	(-0.67)	(0.67)	(-11.66)	(-1.45)
Share of employment in routine jobs	0.0322	0.00221	-0.0137	0.0137	-54359.4**	25956.6
	(0.93)	(0.07)	(-0.36)	(0.36)	(-3.19)	(1.63)
Imports from China to the U.S.	-5.61e-11	-4.03e-11	-2.72e-10	2.72e-10	-0.00000814	0.00000687
	(-0.31)	(-0.23)	(-1.54)	(1.54)	(-0.09)	(0.08)
Observations	2761	2761	2074	2074	2761	2761
Adjusted R-squared	0.1668	0.0745	0.0562	0.0562	0.4899	0.1979

Notes: The models are estimated in the commuting zone level and the weighted total votes of different parties are weighted by the commuting zone population. The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).

The fourth table presents FE estimates of the change in exposure to robots on US presidential election outcomes. Each column presents different specification of the dependent variable (column 1 and column 2 represents weighted total votes for democrats; column 3 represents weighted total votes of republican; column 4 represents the share of democrats' votes in the U.S. presidential election).

Table A3-4: Panel estimates of the change in exposure to robots on U.S. presidential outcomes from 2000 to 2016 under fixed effect model.

FE estimates for the effect of robot exposure on U.S. presidential election outcomes by using panel data from 2000 to 2016	DEMOPW	DEMOPW	REPUBPW	SDEMO
U.S. robot exposure	-44.06*	92.54***	-43.72**	-62.93*
	(-2.34)	(4.06)	(-2.59)	(-2.03)
Total population	-0.0283***	-0.0725***	-0.0216***	-0.00112
	(-9.85)	(-19.45)	(-8.38)	(-0.41)
Working age population	0.0560	0.340	-0.387***	0.180
	(0.44)	(1.96)	(-3.42)	(1.27)
Black population	0.521*	3.111***	0.189	0.213
	(2.04)	(7.87)	(0.83)	(0.84)
Hispanics population	-0.120*	-0.290***	0.0795	-0.0240
	(-2.29)	(-3.40)	(1.69)	(-0.67)
Share of adults with less than a high school diploma	0.038	1.032***	-0.136	-0.900***
	(0.25)	(4.99)	(-1.00)	(-4.33)
Share of adults with a high school diploma	0.107	0.387	-0.144	0.129
	(0.70)	(1.71)	(-1.05)	(0.66)
Share of adults with a bachelor's degree or higher	-0.127	0.431	0.355*	-0.832***
	(-0.72)	(1.55)	(2.24)	(-3.92)
Employment of construction industry	2.095***	-0.603	-1.713***	-0.0125
	(4.73)	(-0.77)	(-4.32)	(-0.03)
Employment of manufacturing industry	-0.0244	1.252***	-0.339	-0.0194
	(-0.09)	(3.69)	(-1.34)	(-0.05)
Employment of non-tradable industry	-0.649	-0.603	1.125**	-0.320
	(-1.51)	(-1.22)	(2.92)	(-0.50)
Share of employment in routine jobs	-0.0712	-0.424*	0.412***	-0.485**
	(-0.57)	(-2.30)	(3.67)	(-3.06)
Imports from China to the U.S.	5.52e-11	-0.00000323	7.55e-11	-2.37e-10
	(0.27)	(-0.23)	(0.42)	(-1.35)
Four years leads of U.S. robot exposure	✕	✔	✕	✕
Time fixed effects and commuting zone's fixed effect	✔	✔	✔	✔
Observations	2761	686	686	686
Within R-squared	0.2006	0.3627	0.2216	0.4725

Notes: The models are estimated in the commuting zone level and the weighted total votes of different parties are weighted by the commuting zone population. The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).

The fifth table presents RE estimates of the change in exposure to robots on US presidential election outcomes. Each column presents different specification of the dependent variable (weighted total votes for democrats; the share of democrats' votes; weighted total votes of republican; and the share of republican's votes in the US presidential election).

Table A3-5: Panel estimates of the change in exposure to robots on U.S. presidential outcomes from 2000 to 2016 under random effect model.

RE estimates for the effect of robot exposure on U.S. presidential election outcomes by using panel data from 2000 to 2016				
	DEMOPW	SDEMO	REPUBPW	SREPUB
U.S. robot exposure	-59.21***	-55.64**	-1.167	55.64**
	(-4.47)	(-3.01)	(-0.09)	(3.01)
Total population	-0.0198***	0.00270	-0.0161***	-0.00270
	(-10.98)	(1.58)	(-9.28)	(-1.58)
Working age population	0.0546***	-0.0259*	-0.0143	0.0259*
	(4.61)	(-1.97)	(-1.25)	(1.97)
Black population	0.0495	0.0418**	0.00691	-0.0418**
	(3.26)	(2.59)	(0.47)	(-2.59)
Hispanics population	-0.0402***	0.0164*	0.0327**	-0.0164*
	(-3.77)	(2.20)	(3.17)	(-2.20)
Share of adults with less than a high school diploma	-0.00295	-0.0994***	0.0671**	0.0994***
	(-0.14)	(-3.99)	(3.26)	(3.99)
Share of adults with a high school diploma	-0.0565	-0.161***	-0.0528	0.161***
	(-1.94)	-4.87)	(-1.88)	(4.87)
Share of adults with a bachelor's degree or higher	0.0551	0.000441	-0.0333	-0.000441
	(1.60)	(0.01)	(-1.00)	(-0.01)
Employment of construction industry	2.036***	0.319	0.803***	-0.319
	(10.81)	(1.53)	(4.41)	(-1.53)
Employment of manufacturing industry	0.0700	0.335***	0.242**	-0.335***
	(0.78)	(3.42)	(2.79)	(-3.42)
Employment of non-tradable industry	-0.944***	-0.114	-0.0749	0.114
	(-6.04)	(-0.67)	(-0.50)	(0.67)
Share of employment in routine jobs	0.0322	-0.0137	0.00221	0.0137
	(0.93)	(-0.36)	(0.07)	(0.36)
Imports from China to the U.S.	-5.61e-11	-2.72e-10	-4.03e-11	2.72e-10
	(-0.31)	(-1.54)	(-0.23)	(1.54)
Observations	2761	2074	2761	2074
Within R-squared	0.0816	0.0042	0.0471	0.0042

Notes: The models are estimated in the commuting zone level and the weighted total votes of different parties are weighted by the commuting zone population. The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).

The next table presents the result of the hausman test based on the model that uses the weighted total votes of democrats (DEMOPW)as the dependent variable.

Table A3-6: The result of Hausman test

```
Test:  Ho:  difference in coefficients not systematic

              chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                      =      155.15
            Prob>chi2 =      0.0000
            (V_b-V_B is not positive definite)
```

The following table shows the first stage regression result of the U.S. presidential election by regressing the U.S. robot exposure on EU robot exposure and all other control variables.

Table A3-7: The first stage regression result of the U.S. presidential election from 2000 to 2016 by using the panel data

First stage regression results: dependent variable is U.S. robot exposure	
	ROBOTUS
EU robot exposure	0.1628475*** (-0.0035415)
Total population	8.81e-09*** (1.78e-09)
Working age population	7.30e-08*** (1.34e-08)
Black population	3.66e-08** (1.68e-08)
Hispanics population	4.63e-08*** (8.01e-09)
Share of adults with less than a high school diploma	-0.0012422*** (0.0002445)
Share of adults with a high school diploma	-0.0000935 (0.0003293)
Share of adults with a bachelor's degree or higher	-0.0006451 -0.0003971
Employment of construction industry	-4.17e-06*** (1.98e-07)
Employment of manufacturing industry	2.46e-06*** (8.05e-08)
Employment of non-tradable industry	1.08e-06*** (1.72e-07)
Share of employment in routine jobs	-0.2290482*** (0.039454)
Imports from China to the U.S.	-2.86e-17 (2.08e-16)
Observations	2878
Adjusted R-squared	0.9154

The following table presents the second stage regression results of the U.S. presidential election by using the EU robot exposure as the instrument of the U.S. robot exposure. Each column presents different specification of the dependent variable (weighted total votes for democrats; the share of democrats' votes; and the share of republican's votes in the US presidential election).

Table A3-8: The second stage regression result of the U.S. presidential election from 2000 to 2016 by using the panel data

The second stage estimates for the effect of robot exposure on U.S. presidential election by using panel data from 2000 to 2016				
	DEMOPW	DEMO	REPUBPW	REPUB
U.S. robot exposure	-58.01**	-1.18e-08***	-53.2429***	254600*
	(-2.90)	(-12.37)	(-2.75)	(0.03)
Total population	-0.0198***	-1321.3	-0.0161709***	-989.0573
	(-11.00)	(-1.73)	(-9.28)	(-1.38)
Working age population	0.0545***	28155.18***	-0.0132957	6501.521
	(4.62)	(4.98)	(-1.16)	(1.23)
Black population	0.0492**	8258.159	0.0200907	-15999.38*
	(3.15)	(1.14)	(1.33)	(-2.35)
Hispanics population	-0.0403***	-14002.7***	0.0345829***	-25038.77***
	(-3.78)	(-4.11)	(3.35)	(-7.82)
Share of adults with less than a high school diploma	-0.00277	-13019.07	0.0591038*	6743.259
	(-0.13)	(-1.24)	(2.86)	(0.68)
Share of adults with a high school diploma	-0.0564	-12567	-0.0531383	-44365.64***
	(-1.94)	(-0.88)	(-1.89)	(-3.31)
Share of adults with a bachelor's degree or higher	0.0552	-3758.274	-0.0369321	-46683.08*
	(1.61)	(-0.22)	(-1.11)	(-2.93)
Employment of construction industry	2.039***	1732124***	0.6397234***	752647.4***
	(10.53)	(18.65)	(3.41)	(8.63)
Employment of manufacturing industry	0.0645	627151***	0.4845087***	51153.63
	(0.57)	(12.07)	(-0.50)	(1.05)
Employment of non-tradable industry	-0.943***	-855236.8***	-0.0759141	-113016.4
	(-6.05)	(-11.68)	(-0.50)	(-1.54)
Share of employment in routine jobs	0.0326	-0.0710	-0.0169957	33933.34*
	(0.93)	(-3.15)	(-0.50)	(2.11)
Imports from China to the U.S.	-5.60e-11	-2.76e-10	-4.32e-11	8.03e-06
	(0.27)	(-0.09)	(-0.25)	(0.10)
Observations	2761	2767	2761	2767
Within R-squared	0.1708	0.4923	0.0733	0.1971

The following table presents IV estimates of the change in exposure to robots on US presidential election outcomes with fixed effect. Each column presents different specification of the dependent variable (weighted total votes for democrats; the share of democrats' votes; weighted total votes of republican; and the share of republican's votes in the U.S. presidential election).

Table A3-9: Panel estimates of the change in exposure to robots on U.S. presidential outcomes from 2000 to 2016 with fixed effect under IV regression.

IV estimates for the effect of robot exposure on U.S. presidential election outcomes by using panel data with fixed effect				
	DEMO	REPUB	REPUBPW	REPUB
U.S. robot exposure	-126940943.2***	-97143624.2***	10.75	-70.66***
	(-13.05)	(-10.94)	(0.48)	(-3.53)
Total population	-4742.4***	-1351.5	-0.0292***	-0.0212***
	(-3.77)	(-1.18)	(10.10)	(-8.19)
Working age population	246381.7***	-702027.0***	0.106	-0.412***
	(4.85)	(-15.15)	(0.84)	(-3.62)
Black population	-850726.8***	-52238.7	0.548*	0.176
	(-8.87)	(-0.58)	(2.14)	(0.77)
Hispanics population	-10792.0	-79810.2***	-0.156**	0.0970*
	(-0.70)	(-5.71)	(-2.93)	(2.04)
Share of adults with less than a high school diploma	-106273.0	87849.7	0.0388	-0.136
	(-1.61)	(1.46)	(0.26)	(-1.01)
Share of adults with a high school diploma	-9271.7	35241.1	0.105	-0.143
	(-0.14)	(0.58)	(0.68)	(-1.04)
Share of adults with a bachelor's degree or higher	-84129.7	79707.4	-0.163	0.373*
	(-1.09)	(1.13)	(-0.92)	(2.35)
Employment of construction industry	4548271.0***	-1657218.0***	2.275***	-1.801***
	(25.65)	(-10.24)	(5.11)	(-4.52)
Employment of manufacturing industry	-81946.8	-878191.0***	-0.211	-0.242
	(-0.69)	(-8.05)	(-0.77)	(-0.95)
Employment of non-tradable industry	-640006.7***	1277551.7***	-0.597	1.100**
	(-3.54)	(7.74)	(-1.39)	(2.85)
Share of employment in routine jobs	21698.6	7267.6	-0.0478	0.400***
	(0.40)	(0.15)	(-0.38)	(3.56)
Imports from China to the U.S.	0.0000175	-0.000000478	6.00e-11	7.31e-11
	(0.20)	(-0.01)	(0.30)	(0.40)
Time fixed effects and commuting zone's fixed effect	✔	✔	✔	✔
Observations	2767	2767	2761	2761
Within R-squared	0.5634	0.4446	0.1973	0.2201

Notes: The models are estimated in the commuting zone level and the weighted total votes of different parties are weighted by the commuting zone population. The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).

The following table presents IV estimates of the change in exposure to robots on U.S. presidential election outcomes with fixed effect and leads (the US robot exposure in the next four years). Each column presents different specification of the dependent variable (weighted total votes for democrats; the share of democrats' votes; weighted total votes of republican; and the share of republican's votes in the U.S. presidential election).

Table A3-10: Panel estimates of the change in exposure to robots on U.S. presidential outcomes from 2000 to 2016 with fixed effect and leads under IV regression.

IV estimates for the effect of robot exposure on U.S. presidential election outcomes by using panel data with fixed effect and leads				
	DEMO	REPUB	DEMOPW	REPUBPW
U.S. robot exposure	-19708134.8*	-150039140.2***	124.7***	-53.85*
	(-2.53)	(-17.15)	(5.00)	(-2.16)
Total population	-3131.4**	-1514.5	-0.0730***	-0.0354***
	(-2.67)	(-1.15)	(-19.56)	(-9.49)
Working age population	-80135.1	-546847.6***	0.381*	-0.122
	(-1.54)	(-9.37)	(2.18)	(-0.70)
Black population	984600.1***	-391787.3**	3.190***	-0.453
	(8.82)	(-3.12)	(8.05)	(-1.14)
Hispanics population	219757.9***	-170700.4***	-0.318***	0.172*
	(11.21)	(-7.75)	(5.02)	(2.01)
Share of adults with less than a high school diploma	208334.7**	14761.0	1.038***	-0.559**
	(3.23)	(0.20)	(-3.70)	(-2.71)
Share of adults with a high school diploma	-21290.2	135642.3	0.382	-0.0168
	(-0.30)	(1.71)	(1.69)	(-0.07)
Share of adults with a bachelor's degree or higher	176589.7*	160035.3	0.400	0.761**
	(2.03)	(1.64)	(1.44)	(2.74)
Employment of construction industry	364270.8	969308.6***	-0.832	-4.640***
	(1.55)	(3.67)	(-1.06)	(-5.92)
Employment of manufacturing industry	-770361.0***	-655678.7***	1.130***	0.0471
	(-7.27)	(-5.51)	(3.30)	(-5.92)
Employment of non-tradable industry	358361.4*	551946.0**	0.506	1.925***
	(2.36)	(3.24)	(-1.02)	(-3.88)
Share of employment in routine jobs	-91622.5	-25349.4	-0.408*	0.173
	(-1.58)	(-0.39)	(-2.21)	(0.94)
Imports from China to the U.S.	0.140	0.561	-0.00000304	0.00000490
	(0.03)	(0.11)	(-0.21)	(0.34)
Four years leads of U.S. robot exposure	✔	✔	✔	✔
Time fixed effects and commuting zone's fixed effect	✔	✔	✔	✔
Observations	2074	2074	2070	2070
Within R-squared	0.6168	0.6742	0.3618	0.3071

Notes: The models are estimated in the commuting zone level and the weighted total votes of different parties are weighted by the commuting zone population. The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).

The next table presents estimates of the change in exposure to robots on the U.S. congressional election outcomes by using the panel data from 2000 to 2016. Each column presents different specification of the dependent variable (total votes of republican; weighted total votes of republican; weighted total votes for democrats; the share of republican's votes;

total votes of democrats; weighted total votes of democrats and the share of democrats' votes in the U.S. congressional election). Different panel denotes different estimation model.

Table A3-11:Regression results of robots' effect on the U.S. congressional election from 2000 to 2016

	Panel A: OLS estimates					
	REPUB	REPUBPW	SREPUB	DEMO	DEMOPW	SDEMO
U.S. robot exposure	1.14e+07***	-25.70821	5.555788	4061764	5.586342	-5.555787
	(3.52)	(-0.2)	(0.54)	(1.37)	(0.06)	(-0.54)
All covariates	✔	✔	✔	✔	✔	✔
Observations	1243	1243	1151	1155	1155	1151
Adjusted R-squared	0.1581	0.0358	0.1608	0.1138	0.0583	0.1608

	Panel B: Fixed effects estimates					
	REPUB	REPUBPW	SREPUB	DEMO	DEMOPW	SDEMO
U.S. robot exposure	6065713*	-17.40382	-1.820366	-107209	4.503201	1.820368
	(1.67)	(-0.53)	(-0.16)	(-0.03)	(0.09)	(0.16)
All covariates	✔	✔	✔	✔	✔	✔
Time fixed effects and commuting zone's fixed effect	✔	✔	✔	✔	✔	✔
Observations	1243	1243	1151	1155	1155	1151
Within R-squared	0.1466	0.4844	0.113	0.3456	0.2774	0.113

	Panel C: IV estimates					
	REPUB	REPUBPW	SREPUB	DEMO	DEMOPW	SDEMO
U.S. robot exposure	1.82e+07***	49.63458	29.28685**	-2551151	-31.09791	-29.28685
	(5.30)	(1.45)	(2.74)	(-0.77)	(-0.49)	(-2.74)
All covariates	✔	✔	✔	✔	✔	✔
Observations	1243	1243	1151	1155	1155	1151
Within R-squared	0.0652	0.1336	0.0108	0.1865	0.1065	0.1966

	Panel D: IV estimates with fixed effects					
	REPUB	REPUBPW	SREPUB	DEMO	DEMOPW	SDEMO
U.S. robot exposure	8423303*	-.6185613	9.17123	-2749487	107.5972	-9.171226
	(1.72)	(-0.01)	(0.61)	(-0.65)	(1.28)	(-0.61)
All covariates	✔	✔	✔	✔	✔	✔
Time fixed effects and commuting zone's fixed effect	✔	✔	✔	✔	✔	✔
Observations	1243	1243	1151	1155	1155	1151
Within R-squared	0.1462	0.481	0.112	0.345	0.2093	0.112

Notes: The models are estimated in the commuting zone level and the weighted total votes of different parties are weighted by the commuting zone population. The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).

The next table summarizes the regression result of robot exposure on total votes of democrats in the 2000's 2004's 2008's and 2012's U.S. presidential elections respectively. Each row represents that effect of robots in six U.S. states (Michigan, Ohio, Indiana, Illinois, California and New York) that have relatively higher robot exposure. "+" ("-") means positive (negative) effect of robot exposure on total votes of democrats and "sig" ("insig") in the bracket shows the effect is significant (insignificant) at 1/5/ 10 percent significance level.

Table A3-12: Sub-periods cross sectional regression result of DEMO

DEMO	2000	2004	2008	2012
whole Data	- (sig)	+ (insig)	+ (insig)	- (sig)
Michigan	- (sig)	- (sig)	- (sig)	- (sig)
Ohio	- (sig)	+ (insig)	+ (insig)	- (sig)
Indiana	- (sig)	- (sig)	- (sig)	- (sig)
Illinois	- (sig)	- (sig)	- (sig)	- (sig)
Califonia	- (sig)	- (sig)	- (sig)	- (sig)
New York	- (sig)	- (sig)	- (sig)	- (sig)

The following table summarizes the regression result of robot exposure on total votes of republican in the 2000's 2004's 2008's and 2012's U.S. presidential elections. Each row represents that effect of robots in six U.S. states (Michigan, Ohio, Indiana, Illinois, California and New York) that have relatively higher robot exposure. "+" ("-") means positive (negative) effect of robot exposure on total votes of democrats and "sig" ("insig") in the bracket shows the effect is significant (insignificant) at 1/5/ 10 percent significance level.

Table A3-13: Sub-periods cross sectional regression result of REPUB

REPUB	2000	2004	2008	2012
whole Data	- (sig)	+ (insig)	- (sig)	+ (sig)
Michigan	- (sig)	- (sig)	- (insig)	+ (insig)
Ohio	- (sig)	+ (insig)	- (sig)	+ (sig)
Indiana	- (sig)	+ (sig)	- (sig)	+ (sig)
Illinois	- (insig)	- (sig)	+ (sig)	+ (sig)
Califonia	- (sig)	+ (insig)	- (sig)	+ (sig)
New York	- (sig)	- (sig)	- (sig)	- (sig)

The next table summarizes the regression result of robot exposure on weighted total votes of democrats in the 2000's 2004's 2008's and 2012's U.S. presidential elections. Each row represents that effect of robots in six U.S. states (Michigan, Ohio, Indiana, Illinois, California and New York) that have relatively higher robot exposure. "+" ("-") means positive (negative) effect of robot exposure on total votes of democrats and "sig" ("insig") in the bracket shows the effect is significant (insignificant) at 1/5/ 10 percent significance level.

Table A3-14: Sub-periods cross sectional regression result of DEMOPW

DEMOPW	2000	2004	2008	2012
whole Data	- (sig)	+ (sig)	- (sig)	- (sig)
Michigan	- (sig)	+ (sig)	- (sig)	- (sig)
Ohio	- (sig)	+ (sig)	- (sig)	- (sig)
Indiana	- (sig)	+ (sig)	- (sig)	- (sig)
Illinois	- (sig)	+ (sig)	- (sig)	- (sig)
Califonia	- (sig)	+ (sig)	- (sig)	- (sig)
New York	- (sig)	+ (sig)	- (sig)	- (sig)

The following table summarizes the regression result of robot exposure on weighted total votes of republican in the 2000's 2004's 2008's and 2012's U.S. presidential elections. Each row represents that effect of robots in six U.S. states (Michigan, Ohio, Indiana, Illinois, California and New York) that have relatively higher robot exposure. "+" ("-") means positive (negative) effect of robot exposure on total votes of democrats and "sig" ("insig") in the bracket shows the effect is significant (insignificant) at 1/5/ 10 percent significance level.

Table A3-15: Sub-periods cross sectional regression result of REPUBPW

REPUBPW	2000	2004	2008	2012
whole Data	- (sig)	+ (sig)	- (sig)	+ (sig)
Michigan	- (sig)	+ (sig)	- (sig)	+ (sig)
Ohio	- (sig)	+ (sig)	- (sig)	+ (sig)
Indiana	- (sig)	+ (sig)	- (sig)	+ (sig)
Illinois	- (sig)	+ (sig)	- (insig)	+ (sig)
Califonia	- (sig)	+ (sig)	- (sig)	+ (sig)
New York	- (sig)	+ (sig)	- (sig)	+ (sig)

The following table summarizes robustness check result of robot exposure on weighted total votes of democrats in the U.S. presidential election. Column (1) shows the result under OLS estimation and column (2) presents the result under IV estimation. Panel A shows the result from the baseline regression and we want to prove this result is robust. Panel B presents the result by using different specification of robot exposure (excluding data from the automotive industry) and Panel C display the result by adding the robot exposure in automotive industry as an additional control variable.

Table A3-16: Robustness check result of robot exposure on weighted total votes of democrats in the U.S. presidential election.

	Robustness Check of Robot Exposure on DEMO	
	(1) Pooled model	(2) IV model
	Panel A. Baseline specification	
Change in exposure of robots from 2000 to 2016	-1.18e+08***	-1.97e+08*
	Panel B. Different specification of robot exposure	
Change in exposure of robots from 2000 to 2016	-1.18e+08***	-1.17e+08***
	Panel C. Different controls	
Change in exposure of robots from 2000 to 2016	-1.11e+08***	-1.18e+08***

Notes: The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).

The following table summarizes robustness check result of robot exposure on total votes of republican in the U.S. congressional election. Panel A shows the result from the baseline regression and we want to prove this result is robust. Panel B presents the result by using different specification of robot exposure (excluding data from the automotive industry) and Panel C display the result by adding the robot exposure in automotive industry as an additional control variable.

Table A3-17: Robustness check result of robot exposure on total votes of republican in the U.S. congressional election.

	Robustness Check of Robot Exposure on REPUB in pooled model
	Panel A. Baseline specification
Change in exposure of robots from 2000 to 2016	1.24e+07***
	Panel B. Different specification of robot exposure
Change in exposure of robots from 2000 to 2016	1.23e+07***
	Panel C. Different controls
Change in exposure of robots from 2000 to 2016	1.11e+07***

Notes: The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).

The next two figures provides evidence that EU robot exposure can be used as a valid instrument of U.S. robot exposure. Figure A3-1 shows the correlation between EU robot exposure and U.S. robot exposure in two different periods. Figure A3-2 presents the correlation between EU robot exposure and dependent variables (weighted total votes for democrats; weighted total votes of republican; the share of democrats' votes; and the share of republican's votes in the U.S. presidential election).

Figure A3-1: Correlation of changes in exposure of robots in industry level between U.S. and EU

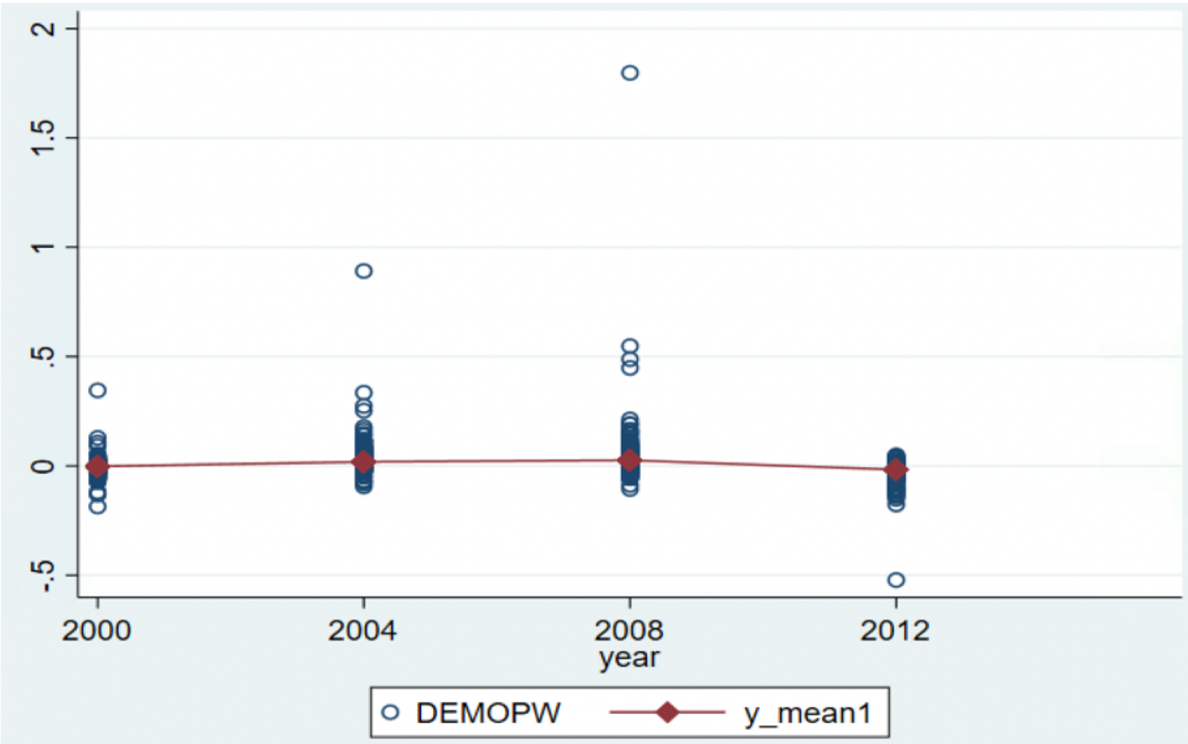
Correlation	US exposure from 2000 to 2008	US exposure from 2000 to 2016
EU exposure from 2000 to 2008	0.973	
EU exposure from 2000 to 2016		0.963

Figure A3-2: Correlation between the instrument (robots exposure in Europe) and each dependent variables.

Correlation	DEMOPW	REPUBPW	SDEMO	SEREPUB
EU robot exposure	0.0302	0.0378**	0.0085	-0.0085

The last figure shows the visual heterogeneity analysis across years for the model that uses DEMOPW (weighted total votes of democrats) as the dependent variable. The red points in Figure A3-3 represents the mean of democrat's total votes each year.

Figure A3-3: Heterogeneity analysis across years



The following part shows different equations used in regressions of the main text.These equations has different dependent variables and same independent variables. Dependent variables include the total votes of Democrats (DEMO), weighted total votes of Democrats (DEMOPW), the total votes of Republicans (REPUB), weighted total votes of Republicans (REPUBPW), the share of Democrats' votes (SDEMO), the share of Republicans' votes (SREPUB). Remaining independent variables are same in these six models, where where ROBOTUS signifies the change of robot exposure in the United States, CONSTRUCT denotes employment of the construction sector, MANUFACT denotes employment of the manufacturing sector, NONTRADE refers to employment of the non-tradable sector, IMPORTCN indicates imports from China to the United States, GDP shows gross domestic products, INC signifies real income per capita, POP indicates the total population, WORKING denotes the working-age population, BLACK represents the black population, HISPANIC signifies the Hispanics population, EDUC1 refers to the share of adults with less than a high school diploma, EDUC2 shows the share of adults with a high school diploma and EDUC3 signifies the share of adults with a bachelor's degree or higher degree.

$$\begin{aligned} DEMO_{ct} = \beta_c + \beta_{1ct}ROBOTUS_{ct} + \beta_{2ct}POP_{ct} + \beta_{3ct}WORKING_{ct} \\ +\beta_{4ct}BLACK_{ct} + \beta_{5ct}HISPANIC_{ct} + \beta_{6ct}CONSTRUCT_{ct} + \beta_{7ct}MANUFACT_{ct} \\ +\beta_{8ct}NONTRADE_{ct} + \beta_{9ct}IMPORTCN_{ct} + \beta_{10ct}IMPORTCN_{ct} + \beta_{11ct}EDUC1_{ct} \\ +\beta_{12ct}EDUC2_{ct} + \beta_{13ct}EDUC3_{ct} + \epsilon_{ct} \end{aligned} \tag{5}$$

$$\begin{aligned} DEMOPW_{ct} = \beta_c + \beta_{1ct}ROBOTUS_{ct} + \beta_{2ct}POP_{ct} + \beta_{3ct}WORKING_{ct} \\ +\beta_{4ct}BLACK_{ct} + \beta_{5ct}HISPANIC_{ct} + \beta_{6ct}CONSTRUCT_{ct} + \beta_{7ct}MANUFACT_{ct} \\ +\beta_{8ct}NONTRADE_{ct} + \beta_{9ct}IMPORTCN_{ct} + \beta_{10ct}IMPORTCN_{ct} + \beta_{11ct}EDUC1_{ct} \\ +\beta_{12ct}EDUC2_{ct} + \beta_{13ct}EDUC3_{ct} + \epsilon_{ct} \end{aligned} \tag{6}$$

$$\begin{aligned} REPUB_{ct} = \beta_c + \beta_{1ct}ROBOTUS_{ct} + \beta_{2ct}POP_{ct} + \beta_{3ct}WORKING_{ct} \\ +\beta_{4ct}BLACK_{ct} + \beta_{5ct}HISPANIC_{ct} + \beta_{6ct}CONSTRUCT_{ct} + \beta_{7ct}MANUFACT_{ct} \\ +\beta_{8ct}NONTRADE_{ct} + \beta_{9ct}IMPORTCN_{ct} + \beta_{10ct}IMPORTCN_{ct} + \beta_{11ct}EDUC1_{ct} \\ +\beta_{12ct}EDUC2_{ct} + \beta_{13ct}EDUC3_{ct} + \epsilon_{ct} \end{aligned} \tag{7}$$

$$\begin{aligned} REPUBPW_{ct} = \beta_c + \beta_{1ct}ROBOTUS_{ct} + \beta_{2ct}POP_{ct} + \beta_{3ct}WORKING_{ct} \\ +\beta_{4ct}BLACK_{ct} + \beta_{5ct}HISPANIC_{ct} + \beta_{6ct}CONSTRUCT_{ct} + \beta_{7ct}MANUFACT_{ct} \\ +\beta_{8ct}NONTRADE_{ct} + \beta_{9ct}IMPORTCN_{ct} + \beta_{10ct}IMPORTCN_{ct} + \beta_{11ct}EDUC1_{ct} \\ +\beta_{12ct}EDUC2_{ct} + \beta_{13ct}EDUC3_{ct} + \epsilon_{ct} \end{aligned} \tag{8}$$

$$
\begin{aligned}
SDEMO_{ct} = \beta_c + \beta_{1ct}ROBOTUS_{ct} + \beta_{2ct}POP_{ct} + \beta_{3ct}WORKING_{ct} \\
+\beta_{4ct}BLACK_{ct} + \beta_{5ct}HISPANIC_{ct} + \beta_{6ct}CONSTRUCT_{ct} + \beta_{7ct}MANUFACT_{ct} \\
+\beta_{8ct}NONTRADE_{ct} + \beta_{9ct}IMPORTCN_{ct} + \beta_{10ct}IMPORTCN_{ct} + \beta_{11ct}EDUC1_{ct} \\
+\beta_{12ct}EDUC2_{ct} + \beta_{13ct}EDUC3_{ct} + \epsilon_{ct}
\end{aligned} \tag{9}
$$

$$
\begin{aligned}
SREPUB_{ct} = \beta_c + \beta_{1ct}ROBOTUS_{ct} + \beta_{2ct}POP_{ct} + \beta_{3ct}WORKING_{ct} \\
+\beta_{4ct}BLACK_{ct} + \beta_{5ct}HISPANIC_{ct} + \beta_{6ct}CONSTRUCT_{ct} + \beta_{7ct}MANUFACT_{ct} \\
+\beta_{8ct}NONTRADE_{ct} + \beta_{9ct}IMPORTCN_{ct} + \beta_{10ct}IMPORTCN_{ct} + \beta_{11ct}EDUC1_{ct} \\
+\beta_{12ct}EDUC2_{ct} + \beta_{13ct}EDUC3_{ct} + \epsilon_{ct}
\end{aligned} \tag{10}
$$

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Appendix 6B: Statement of Authorship

This declaration concerns the article entitled:									
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I hold the copyright for this material	×	Copyright is retained by the publisher, but I have been given permission to replicate the material here							
Candidate's contribution to the paper (provide details, and also indicate as a percentage)	The candidate contributed to / considerably contributed to / predominantly executed the… Formulation of ideas: - Considerably contributed to the formulation of ideas. (70%) Design of methodology: - Predominantly contributed to the design of methodology. (60%) Experimental work: - Predominantly contributed to the experimental work. (80%) Presentation of data in journal format: - Predominantly contributed to the presentation of data in journal format. (70%)								
Statement from Candidate	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature.								
Signed	Diling Xiang	**Date**	18/12/2020						

Chapter 4

Robots and mental health in the United States

Abstract

The stock of industrial robots in the United States experiences a noticeable increase from 12,836 in 2000, to 31,404 in 2016. Indeed, as previously discussed in this paper, robots are replacing tasks once completed by humans, which, in turn, impacts job opportunities in the labour market. Thus, it is vitally important to consider the impact of robots on the mental health of workers. This chapter considers the ways in which the use of robots affects the mental health of workers using "DSA" fatalities. As the first study to explore the effect of robots on mental health in the United States, this empirical study collates industrial robot and mortalities data with IV regression. The main finding of this study is the negative and significant effect of increasing robot exposure on the mental health of workers, which is reflected in increasing fatalities caused by drug, alcohol, and other related factors. Additionally, the possible transmission channel between robots and mental health is discussed in light of political implications. In essence, policy makers and companies ought to pay close attention to the mental health of workers when deepening their use of robots in the workplace.

Keywords: Industrial Robots, Robots, Mental Health, Mental Distress, Mortality, Deaths of Despair.

4.1 Introduction

Robots are used in various industries and contribute to the overall efficiency of production. As a substitute of human resources, robots hold many advantages over human workers; namely, robots do not suffer from fatigue and are easily applied in some high-risk industries. Accordingly, the availability of robots adversely impacts the number of jobs available for humans in the labour market, causing humans to feel stressed, anxious, and isolated while feeling as if their employment status is threatened. Conversely, the development of robots may result in new job opportunities for humans, though a majority of workers still feel their employment conditions are threatened. According to Smith and Anderson (2017) survey as part of the PEW Research Center in the United States, 72 percent of interviewees answered that they were fearful and worried that robots will replace their jobs in the future. Furthermore, the study of Acemoglu and Restrepo (2017) posits that industrial robots have a negative effect on the U.S. labour market, leading to lower employment and wages. As a result, workers may experience mental health issues due to increasing economic pressures caused by lower employment opportunities.

Since 1999, overall life expectancy in the United States has decreased. Hedegaard et al. (2017), state 63,632 American people died due to drug overdose, compared to 16,849 drug-related deaths recorded in 1999. Furthermore, Paulozzi (2012) demonstrates that drug overdose has become the primary cause of injury-related deaths in the United States. Xu et al. (2016) state that poisoning-related deaths, (90 percent caused by drug overdose), significantly influences the decrease in life expectancy in the U.S. Drug-related deaths are more likely caused by intensified pressure and distress from jobs, as employment is highly associated with individuals income level, thereby quality of life.

According to Ghertner and Groves (2018), high unemployment correlates with higher rates of retail opioid sales and deaths caused by drug overdose. Dow et al. (2019)'s study supports this claim, indicating that minimum wage and income tax credit that helps low-income and middle-income workers and families get a tax break are associated with mortality from alcohol poisoning, drug overdose, and suicide, which is also known as the deaths of despair. Lower minimum wage and income tax credit leads to higher number of deaths of despair. Thus, economic conditions can drive the mortality rate. Aliprantis et al. (2019) also note that a decrease in labour opportunities lead to a higher local opioid prescription rate. Most notably, opioid usage tends to be higher in countries with depressing economic outcomes. Afterwards, drug abusers are more likely to move from prescription drugs, to heroin and synthetic drugs, given that the latter have the same effect and are more addictive. Ghertner and Groves (2018) found that deaths caused by drug overdose and opioid abuse are more likely to occur in rural areas with less economic development. Moreover, people with worse economic situations tend to be less educated about opioid and are more likely to be uninsured. Therefore, there is a higher possibility that individuals living in lower socio-economic rural areas will be exposed to the opioid epidemic, leaving them unable to afford medical expenses. In turn, opioid misuse could lead to a decrease in labour force participation, aggregating the disparity of medical resources, and thus forming a negative cycle. The study of Cutler and Lleras-Muney (2010) also finds that opioid misuse and drug fatality rates have sharply risen in rural areas with relatively low overall education levels. In their empirical study, Aliprantis et al. (2019) demonstrate that a 10 percent increase in local opioid is associated with over 0.15 percent decline in labour participation for adults, implicating a negative relationship between drug prescription rates and the rate of employment. In addition, long-term labour market shock tends to have a clear effect on the drugs overdose rate.

The study of Case and Deaton (2015) argues that the loss of a sense of wellbeing is a key influencing factor that leads to drug addiction, alcoholism, and suicide among Americans. As Botelho et al. (2017) state, the American population has experienced a massive turmoil in manufacturing industry. Over the last five decades, the demand for drugs has increased due to a gradual loss of jobs in the manufacturing industry. Some of the counties, which was developed in traditional manufacturing, in the U.S. has suffered selective economic decline. After the economic recession in the United States in 2008, many people suffered from downward mobility; widespread fear and anxiety spread across the country. For many Americans, their hopelessness and despair resulted in turning to drugs and alcohol. The study of Monnat (2016) supports this claim, demonstrating that as economic conditions in the United States worsen, drug and suicide mortality rates increase. Evidently, therefore, robots and automation could significantly affect death rates in America by influencing workers' mental health due to a lack of employment opportunities.

A wealth of research focuses on the influence of robots on the labour market; specifically, the majority of studies investigate the correlation between the U.S. labour market and the health conditions of workers. Conversely, there appears to be a lack of studies that focus on the effect of robots and automation on the health of individuals. Nevertheless, Abeliansky and Beulmann (2019) provide initial evidence of the negative impact industrial robots have on self-reported mental health conditions of workers in Germany. The following section of this paper will explore how the use of industrial robots affects the number of drug and alcohol related deaths, reflecting the mental health of workers in the United States. This paper match mortality data from the *Multiple Cause of Death (MCOD)* and industrial robot data between the years 2000 to 2015 from the International Federation of Robotics (IFR) at the U.S. commuting zone level. This paper finds the increasing usage of industrial robot leads to increasing mortality caused by drug, alcohol and other factors. In essence, this paper investigates the deterioration of American workers' mental health given the rise of automation and industrial robotics.

The remainder of this paper is as follows: section 4.2 introduces the literature on factors affecting the mortality rate and explanations of the deterioration of U.S. mortality rate; section 4.3 portrays the data source and explains the first stage relationship between U.S. robot exposure and the instrument; Section 4.4 explains the empirical specification of the methodology and section 4.5 discusses the main empirical results that the increasing robot usage affect the mental health of workers negatively. In addition, section 4.6 proves this result is robust under different robustness checks and consistent with the finding of Abeliansky and Beulmann (2019). The final section concludes main findings of this paper and related policy suggestions.

4.2 literature review

4.2.1 U.S. mortality rate

The United States experiences an extraordinary long-run decrease in mortality rate, especially for people at middle age and older age (Cutler et al., 2006; Deaton, 2013; Lee and Carter, 1992). Due to the improvements in people's behavior and medical treatment, the mortality rate for age group 45-54 decreases by 44 percent from 1970 to 2013 in the United States and this declining trend can be found in other developed countries (Ford et al., 2007; Cutler, 2005). Decreasing mortality rates means that people are living for longer; notably, however, many people assume that the mortality rate will continue to decline given the rapid development of technologies. As such, a number of studies investigate the recent deterioration of mortality rates for specific age groups and explore the cause of their deaths in the United States.
The situation of the drug epidemic in the United States is serious. In the United States, the number of drug related deaths caused by an drug overdose is almost three times greater in 2016 than in 1999 (Hedegaard et al., 2017). Paulozzi (2012) asserts that drug overdose has become the main cause of injury death, exceeding the number of fatalities caused by motor accidents from 2009. The main explanation for the initial significant growth of drug related deaths is associated with the opioid analgesics (Jones et al., 2013; Paulozzi et al., 2014). However, Hedegaard et al. (2017) find the main causes of drug mortality are synthetic opioids and heroin, which exceeds the drug death due to prescription opioids.

4.2.2 Social and Economic environment

Death of despair

Case and Deaton (2015) report the noticeable rise of deaths of people aged between 45-54 years old due to suicide, chronic liver disease, and drug poisoning since 1998; notably, this reversal is not found in other developed countries that maintain a steady declining mortality rate. Additionally, Case and Deaton (2015) posit that the rapid growth in poison related deaths acts

as a driving force for the decline of life expectancy. As such, deteriorating midlife mortality is associated with rising distress; the increasing consumption of intoxicants is strongly linked to the rapid development of automation and globalization. “Deaths of despair” is defined by Case and Deaton (2017) as a kind of suicide caused by growing distress from the social and economic environment. Specifically, their argument is that an increasing number of mortalities is fundamentally driven by the fluctuating social and economic circumstances, rather than the drugs and opioids. Stiglitz (2015) supports this view and implies that a fairer distribution of wealth would lower mortality caused by suicides, drug overdose, and alcoholic liver disease.
Though it is difficult to prove the rising levels of distress in middle-aged people is directly associated with social and economic indicators, such as income and employment, there are some convincing and meaningful discussions. Case and Deaton (2017) note a parallel trend between increasing inequalities in education and middle-aged health. Furthermore, in the global knowledge and skills economy, people who lack the relevant skills or education are likely to miss out on employment in comparison to educated citizens. Krueger (2017) states that 50 percent of the men take pain medication, and 67 percent of men consume prescription painkiller tablets when losing their jobs. A lack of opportunity or prospect of work undoubtedly affects the mental health of workers as they become increasingly concerned with paying bills, meeting payments, and earning enough to survive. The study ofColantone et al. (2015) demonstrates that the increase of import pressure significantly affects mental health by collating data recorded in the United Kingdom. In addition, he explains the channel between import competition and increasing distress accumulating in the deteriorating labor market environment, such as job replacement and lower payments. According to Emile (1897), if the mental condition and social environment is lower than people’s expectation, they will feel despair and subsequently make choices that adversely affect their health. Thus, economic and social factors undoubtedly affect the mental health of individuals, and are one of the original causes of the increasing mortality rate; as distress and feelings of contempt increase, there is a higher possibility of individuals endangering themselves by taking actions to release stress and anxiety by turning to drugs, subsequently increasing the number of deaths of despair.

Economic conditions

Case and Deaton (2015) argue that the number of recorded deaths of white-Americans caused by suicide, alcoholism, and drug abuse significantly increased when challenged by an economic recession. Notably, therefore, this research finding supports the claim that an individual’s behaviour is likely to change in worsening economic situations. A great deal of research supports the correlation between economic recessions and health outcomes and is consistent with Case and Deaton’s hypothesis. Nonetheless, job cuts and unemployment undoubtedly have negative effects on the health of individuals, increasing the number of poor health choices people make, such as the consumption of cigarettes (Bergemann et al., 2011; Black et al., 2015; Browning et al., 2006).

Conversely, a large proportion of research argues that the relationship between general economic conditions and health outcomes is counter-cyclical. Some research suggests individuals' health conditions improve at the time of economic recessions due to an increased amount of leisure time to participate in physical activities and other healthy behaviours (Ruhm, 2000). Data collection of Asgeirsdottir et al. (2014) in Iceland proved that the economic crisis in 2008 positively impacted individuals' health conditions and behaviour choices. In this light, the link between decreasing unemployment and health conditions becomes questionable – a link, however, that must not be ignored.

The results of recent researches that examine the relationship between economic circumstance and opioid addiction are ambiguous. The deterioration of the economic condition, such as increasing unemployment and harmful trade strike, is associated with rising opioid consumption and deaths (Hollingsworth et al., 2017; Carpenter et al., 2017; Pierce and Schott, 2016). However, Ruhm (2018) asserts that the change of macroeconomic conditions is only responsible for one-ninth of the increase of drug-caused mortalities.

On the contrary, the causal relationship between economic conditions and opioid overdose is examined in the opposite direction. Although the study was descriptive rather than analytical, the Organization of Economic Cooperation and Development announced that opioid abuse is one of the main causes of decreasing labor participation in the United States (OECD, 2018). Krueger (2017), however, supported this claim by providing empirical evidence that opioid prescription and unemployment rates for men were at its highest between 1999 to 2015; notably, however, the trend of decreasing labour participation already existed before the opioid epidemic. Additionally, Currie et al. (2018) note a small and positive effect of opioid prescription on female's employment rates, with no recorded significant effect on males. This suggests that opioid prescription is helpful to the woman's participation in the U.S. labour market. Moreover, Currie et al. (2018) also note an ambiguous influence of employment on opioid prescription; employment circumstances appeared to adversely affect opioid prescription rates significantly for youthy adults in well-educated counties.

Social status and health inequality

Case and Deaton (2017) hypothesize that the deteriorated labor market condition is one of the important determinants of increasing drug consumption and alcohol abuse due to stress. This hypothesis is consistent with other research highlighting the causal effect of social status and comparisons of mental distress and health inequalities. Kessler (1979) summarizes the relationship between disadvantaged social status and mental illness, using the terms intrapsychic tendency and the social environment impact. Disadvantaged social statuses and life conditions are likely to cause stressful experiences. Moreover, these people are more likely influenced by stressful experiences given the lack of access to coping mechanisms. Accordingly, Wilkinson (1997) outlines the psychosocial influences of social conditions as important explanations of health inequalities, such as smoking, drinking alcohol, and drug consumption due to stress.

Many studies observe the social-economic variations in a series of mental illnesses, such as depression and anti-social personality. Evidence indicates that people with lower socio-economic status are more likely to suffer from a mental illness (Dohrenwend, 1990; Bruce et al., 1991; Dohrenwend et al., 1992; Kessler et al., 1994; Lewis et al., 1998). Two main explanations for differences in health conditions between socio-economic groups exist: health selection hypothesis and social causation. Firstly, health selection hypothesis refers to the process in which people with poor health conditions gradually fall behind in the social hierarchy (Dohrenwend et al., 1992). Most notably, the selection effect portrays different strengths across each stage of life; psychological disorders begin to influence individuals during their time spent in education, and, in turn, educational attainment marks individuals' social status (Caspi et al., 1990; Kuh et al., 1997). Thus, the selection effect may increase in prominence as young people enter the labor market while establishing their social status (Power et al., 2002).

Secondly, social causation is the other explanation of how health is affected by social status. People in lower social positions tend to suffer more from stressors and difficulties, than people with high social status (Power and Matthews, 1997). During an individual's childhood and early adolescence, their social status is usually determined by their parents or carers; the family environment is often important in the development of a child's emotional well-being (Offord et al., 1992). According to Lundberg (1991) and Weich et al. (1998), social causation correlates to material condition during childhood and adult life. People in poor families receive adverse effect on psychological health when comparing the material conditions with those advantaged people. In addition, people may suffer from mental health issues due to pressures or stresses from school or because of a strained relationship with family members at home. Therefore, material condition correlates with mental health issues both directly and indirectly.

Furthermore, social relationships in adult life become a crucial factor of social causations effect on the psychological health of adults (Turner and Marino, 1994). Socio-economic status is undoubtedly affected by social networks that are established in adult life. Before adulthood however, Bloom et al. (1978) and Kitson and Morgan (1990) assert that people with divorced and separated parents are more likely to suffer from psychiatric stress. Additionally, single mothers and women experiencing teenage pregnancy are more likely to suffer from psychological distress (Brown and Harris, 2012; Lipman et al., 1997; Weich and Lewis, 1998). In essence, people without positive social relationships to fall back on for emotional support and care are more likely to experience psychological distress (Oxman et al., 1992).

Finally, the labour market environment also partly explains the differences in health conditions across different socio-economic groups from the aspect of social causation. For instance, a wealth of research demonstrates the associated impact of unemployment and job insecurity on mental health conditions, or even suicide (Burchell, 1990; Ferrie et al., 1998; Gunnell et al., 1999).

4.2.3 Drug environment

Poison-related deaths are the most significant cause of the decreasing life expectancy of middle-life whites in the United States since 1999; more than 90 percent of poison-related deaths are caused by drugs (Case and Deaton, 2015). Besides the "deaths of despair" hypothesis, the drug environment is another alternative explanation of increasing mortality rates in the U.S. In relation to the drug environment hypothesis, drug fatalities of white Americans is considered a more serious issue than other ethnicities given the wide prescription of opioid to white Americans (Green et al., 2009; Burgess et al., 2014; Singhal et al., 2016). Notably, the United States holds a large share of opioid consumption around the world, arguably resulting in higher mortality rates in the United States compared to other countries. The study of Cutler and Lleras-Muney (2010) implies that people in rural areas with a low level of education may be at a higher risk of dying from drug abuse as they may lack information about the potential harm. Furthermore, Paulozzi et al. (2011) state opioid pain relievers relate to 73.8 percent of recorded deaths caused by prescription drug abuse in 2008. The involvement of opioid in treatment attribute to the availability of opioid, and then the risk of overdoes. Availability of opioids in the United States becomes relatively high due to prescriptions (Paulozzi et al., 2011), influxion of heroin and unlawful synthetic opioids (Frank and Pollack, 2017; Cicero et al., 2015); as such, the number of individuals who suffer from opioid disorder problems increases (Han et al., 2015). Moreover, opioid is also associated with the risk of suicide; opioids were directly involved in more than 40 percent of deaths caused by suicide and drug overdose in 2017 (Bohnert and Ilgen, 2019).

4.3 Data description and first stage

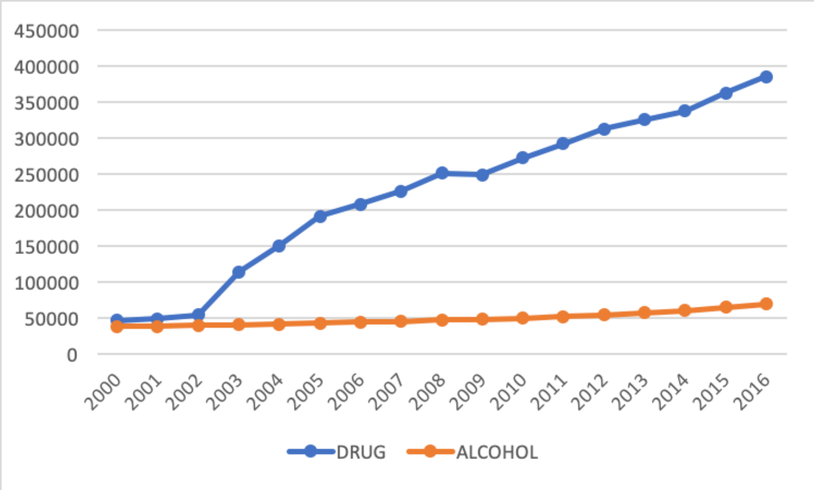
This paper aims to explore the effect of industrial robots on the mental health of American people by linking robot stock data from the International Federation of Robotics and "deaths of despair" data from the U.S. Centers for Disease Control and Prevention at the commuting zone level. Utilising Tolbert and Sizer (1996) classification, 722 commuting zones exist; every commuting zone is assigned a specific value related to the stock and exposure of robots for each year. The purposes of this section are as follows. Firstly, all data sources of this study's variables used in the regression model will be explained and subsequently outlined in Table4-1.

Secondly, the process in which the author has chosen to measure robot exposure is explained. Third, the first stage of the relationship between the exposure of U.S. robots and the proxy that uses the exogenous robot exposure from eight European countries is explored. Finally, panel data from the commuting zone level between 2000-2015 is analysed for the regression analysis.

4.3.1 Dependent Variables: mortality data

According to the "deaths of despair" theory, DSA fatalities are caused by drug overdose, suicide, and alcoholic liver disease. Notably, Case and Deaton (2015) suggest the increases in "deaths of despair" correlates with the considerable increase in mental distress. Therefore, drug and alcohol related mortality are the dependent variables in this paper, which have also been used to measure psychological pressures in a number of other studies (Ghertner and Groves, 2018; Dow et al., 2019; Cutler and Lleras-Muney, 2010). Data is collected from the *Multiple Cause of Death (MCOD)* files, which can be downloaded from the Centers for Disease Control and Prevention. This MCOD file includes the county-level national mortality and demographic data from 1999 to 2016 and data are based on death certificates for U.S. residents. Each death certificate contains a single underlying cause of death, up to twenty additional multiple causes (4 digit ICD-10 codes, 113 selected causes of death, 130 selected causes of infant death, drug and alcohol related causes of death, injury intent and injury mechanism categories), place of residence (national, region, division, state, and county), age (single-year-of age, 5-year age groups, 10-year age groups and infant age groups), race (American Indian or Alaskan Native, Asian/Pacific Islander, Black or African American, White), Hispanic ethnicity, gender and year.

Figure 4-1. Mortality caused by drug and alcohol in the United States, 2000-2016



Notes: This figure shows the drug-induced mortality and alcohol-induced mortality in the United States from 2000 to 2016. The data source is the *Multiple Cause of Death (MCOD)* files from the U.S. Centers for Disease Control and Prevention.

This paper selects the drug and alcohol related causes of death, which includes data recording the cause of mortalities such as drug abuse, alcoholism, and all other factors from 2000 to 2016 at the U.S. county level. Moreover, people considered to be a 'working-age' are only included in this study by using a five-year age group classification, which is presented as follows: 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, and 55-59 years old.

Figure4-1 illustrates the change of mortality caused by drug and alcohol in the United States from 2000 to 2016. The blue line represents drug-induced mortalities, demonstrating the dramatic and increasing growth after 2002. Noticeably, the number of recorded deaths caused by drug abuse is 46,894 in 2000 and increases dramatically to 384,680 in 2016. On the other hand, the orange line represents the movement of alcohol-related mortalities; a steady growth appears between 2000 and 2016. The rising number of deaths caused by drug and alcoholism in recent years indicates higher pressure and the deterioration of individuals'mental health.

The dependent variables used in this study are as follows: drug-induced mortality (DRUG); alcohol-induced mortality (ALCOHOL); other-induced mortality (OTHER); annual change of the drug-induced mortality (cDRUG); annual change of alcohol-induced mortality (cALCOHOL); annual change of other-induced mortality (cOTHER). Next, data collected from the county-level must be transformed to the commuting zone level.

The mortality data of each commuting zone is constructed by adding the mortality of every county in that commuting zone at a given year between 2000 to 2016 as the following:

$$DRUG_{ct} = \sum_{i \in \mathcal{I}} drug_{it} \tag{11}$$

$$ALCOHOL_{ct} = \sum_{i \in \mathcal{I}} alcohol_{it} \tag{12}$$

$$OTHER_{ct} = \sum_{i \in \mathcal{I}} other_{it} \tag{13}$$

$$cDRUG_{ct} = DRUG_{ct} - DRUG_{c,t-1} \tag{14}$$

$$cALCOHOL_{ct} = ALCOHOL_{ct} - ALCOHOL_{c,t-1} \tag{15}$$

$$cOTHER_{ct} = OTHER_{ct} - OTHER_{c,t-1} \tag{16}$$

where $drug_{it}$, $alcohol_{it}$, $other_{it}$ represents the drug-induced mortality, alcohol-induced mortality and other-induced mortality for county i at year t.

4.3.2 Independent Variables: robot exposure

U.S. robot exposure (ROBOTUS) is the key independent variable in the analysis. The International Federation of Robotics (IFR) provides reliable data of industrial robot stock in different countries and different industries from 1990s to 2017. Previous studies have collected robot usage data from IFR to explore the effect of robots on different economic aspects (Acemoglu and Restrepo, 2017; Graetz and Michaels, 2018; Abeliansky and Beulmann, 2019). Industrial robot data provided by the IFR covers 90 percent of the market that adopts industrial robots across 50 different countries. Accordingly, the IFR collects industrial robot data by sending surveys to suppliers of robots; eight chosen European countries (Denmark, Finland, France, Germany, Italy, Sweden, United Kingdom and Spain) are selected as a proxy for the exogenous change of U.S. robot exposure. According to the classification of IFR, robots are divided into 19 industries: agricultural; forestry and fishing; mining; food and beverages; textiles; wood and furniture; paper; plastic and chemicals; glass and ceramics; basic metals; metal products; metal machinery; electronics; automotive; other vehicles; other manufacturing industries; utilities; construction; education; research and development; and other non-manufacturing industries. Replicating the study of Acemoglu and Restrepo (2017), robot exposure in the U.S. is constructed by combining the data of industrial robot stock and the employment share at industry level. Notably, this measure reflects the variation of industrial robots deployed in different U.S. commuting zones. The process of constructing the U.S. robot exposure is demonstrated by the following equation:

$$ROBOTUS_{ct} = \sum_{i \in \mathcal{I}} \ell_{ci,t} \left(\frac{R^{US}_{i,t+1}}{L^{US}_{i,t}} - \frac{R^{US}_{i,t}}{L^{US}_{i,t}} \right) \tag{17}$$

where $\ell_{ci,t}$ represents the employment share of industry i in commuting zone c over the total baseline employment and $\left(\frac{R^{US}_{i,t+1}}{L^{US}_{i,t}} - \frac{R^{US}_{i,t}}{L^{US}_{i,t}} \right)$ reflects the difference of industrial robot stock be-

tween two years.
The process of constructing robot exposure can be divided into three steps. Firstly, the employment share of industry i, in commuting zone c, and in year t ($\ell_{ci,t}$) is calculated by using the data from the County Business Patterns (CBP). The employment data from CBP uses the North American Industry Classification System (NAICS). Fortunately, NAICS code can be matched with the IFR industry classification. Secondly, the industrial robot per worker is calculated by dividing industrial robot data by the employment data of USKLEMS and EUKLEMS. Finally, robot exposure is measured by adding the product of employment share and the number of robots per worker for each commuting zone.
The non-metro area in the United States shows great diversity in economic and social characteristic. County boundaries are more likely to reflect political boundaries and are not adequate to delineate local economies. Commuting zones are geographic units that incorporate all metro and non-metro areas in the United States; economic factors and social heterogeneity of non-metropolitan areas may be captured and compared with county boundaries. Thus, commuting zones are often used as geographical units in economic studies that focus on the labor market (Acemoglu and Restrepo, 2017; David and Dorn, 2013)..
Due to the possible issue of endogeneity from omitted variables, this paper uses instrument variables to create exogenous robot exposure in the United States. Based on the studies of David and Dorn (2013), Bloom et al. (2016), and Acemoglu and Restrepo (2017), this paper use the robot exposure in eight European countries as the instrument of the U.S. robot exposure by substituting the U.S. industrial robot stock data as the 35th percentile EU industrial robot stock data. Robot exposure across Europe provides a comparison to assess the numbers of robots in the United States; a correlation which is explained in the following section.

4.3.3 Control Variables

The control variables in this empirical study can be classified into three main types. Notably, panel data at the commuting zone level from 2000 to 2016 is investigated. Seven proxies tied to DSA fatalities and mental health illnesses are incorporated as economic indicators: employment of the construction industry (CONSTRUCT); employment of the manufacturing industry (MANUFACT); employment of the non-tradable sector (NONTRADE) and the percentage of employment of routine jobs (ROUTINE); import from China to the United States (IMPORTCN); Gross domestic product (GDP); and income per capita (INC). These variables are added to capture any external influences from the labor market environment, globalization, and income, on the number of deaths of despair.
Industrial robots are more likely to replace human jobs in the construction industry, the non-tradable industry, and the manufacturing industry. The industrial movement and trend of

these sectors may affect the adoption of industrial robots. Therefore, employment in these industries are controlled by excluding the effects of possible secular changes to industry, to ensure the effect of robot exposure on peoples' mental health is "pure". The County Business Patterns (CBP) provides employment data in these industries across the county; as such, the commuting zone level employment is the total employment of all counties in each commuting zone.

Similarly, different conditions of international trade across commuting zones might be associated with the variation of robot exposure. Globalization and oversea competition motivates companies to decrease their production cost by adopting more automation technologies. The increasing robot exposure in one commuting zone may be correlated with the higher imports in that commuting zone. However, intensified competition between firms and within businesses may result in deteriorating mental health conditions of workers. For instance, Colantone et al. (2015) study notes a positive, significant, and large effect of increasing import competition on the increased mental distress of British workers. As a result, this study controls the Chinese import to the United States by using the similar approach of Acemoglu et al. (2016) as the following:

$$IMPORTCN_{ct} = \sum_{i \in \mathcal{I}} \frac{L_{ict}}{L_{ct}} importcn_{i,t} \tag{18}$$

where $\frac{L_{ict}}{L_{ct}}$ represents the employment share of industry i in commuting zone c and $importcn_{i,t}$ is the real imports from China to the United States of industry i at year t.

The effects of changes in economic factors on health outcomes are broadly discussed in existing literature in the field (Ruhm, 2000; Hollingsworth et al., 2017; Carpenter et al., 2017). Literature suggests that mental distress is very sensitive to variations in general economic conditions such as income and job security. From an individual level, people with lower incomes are more likely to suffer from opioid misuse and disorder than those with higher incomes (Ghertner and Groves, 2018); socially, however, poverty and unemployment worsen the disparity of health resources. As Acemoglu and Restrepo (2017) note, income and employment levels positively correlate with the exposure of robots; nevertheless, the various economic conditions across commuting zones may affect the level of robot exposure in that area. Thus, GDP and income are selected as economic control variables in this study. The U.S. Bureau of Economic Analysis provides county level GDP and income data; data at the commuting zone level is collected by using the sum of data at county level.

Furthermore, additional covariates are controlled to capture the possible influence of confounding variables, such as individual health and lifestyle choices. As such, health and lifestyle choices will inevitably differ in terms of age as people from different population groups may choose different behaviors when they want to relieve stress. According to Ruhm (2018), between the years 1999 to 2011, drug-caused mortalities in the United States are much smaller for people 20-39 and 40-59 years of age than people aged 60 years old. Race and ethnicity may also affect mortalities; drug mortality rates for whites and blacks is higher than Hispanics, and other nonwhites in 1999 in the United States (Ruhm, 2018). Therefore, several basic demographic indicators are controlled in the analysis, which include the total population (POP), the working age population (WORKING), the black population (BLACK) and the Hispanic population (HISPANIC) in the United States. Population related data comes from the United States Census and data at the commuting zone level is generated by using the sum of counties. Additionally, Dow et al. (2019) highlight the steady increase of midlife mortalities for non-Hispanic whites without a bachelor's degree. Most notably, the mortality rate of people without a college degree is greater than people with a college degree (Ruhm, 2018). Individuals with a lower level of education are more vulnerable to drug abuse or addiction as they may lack knowledge about the number of severe risks drug abuse poses to their health. Thus, the share of population by education level is also controlled in the analysis, which consists of: the share of adults who get less than a high school diploma (EDUC1); the share of adults who are educated at high school level only (EDUC2); and the share of adults who obtained a bachelor's degree or higher (EDUC3). The education data at county level is taken from the United States Census, and data at the commuting zone level is generated by using the average share of counties.

Table 4-1. Explanation and data sources of all variables

Variable Name	Definition	Data Source
DRUG	Total number of drug-induced mortality in U.S.	Centers for Disease Control and Prevention
cDRUG	Changes in total number of drug-induced mortality in U.S.	Centers for Disease Control and Prevention
ALCOHOL	Total number of alcohol-induced mortality in U.S.	Centers for Disease Control and Prevention
cALCOHOL	Changes in total number of alcohol-induced mortality in U.S.	Centers for Disease Control and Prevention
OTHER	Total number of other-induced mortality in U.S.	Centers for Disease Control and Prevention
cOTHER	Changes in total number og other-induced mortality in U.S.	Centers for Disease Control and Prevention
ROBOTUS	Changes in exposure of robots in U.S.	IFR, USKLEMS, EUKLEMS, CBP
ROBOTEU	35th percentile of changes in exposure of robots among European countries	IFR, USKLEMS, EUKLEMS, CBP
POP	Total population of commuting zones	United States Census
WORKING	Population at working age of commutinf zones	United States Census
BLACK	Black population of commuting zones	United States Census
HISPANICS	Hispanic population of commutinf zones	United States Census
EDUC1	Percent of adults with less than a high school diploma	United States Census
EDUC2	Percent of adults with a high school diploma only	United States Census
EDUC3	Percent of adults with a bachelor's degree or higher	United States Census
CONSTRUCT	Employments of construction industry of commuting zones	County Business Parterns (CBP)
MANUFACT	Employments of manufacturing industry of commuting zones	CBP
NONTRADE	Employments of non-tradable industry of commuting zones	CBP
ROUTINE	Share of employment in routine jobs	CBP
IMPORTCN	Share of imports from China to the United States	UN Comrade Database
GDP	Real gross domestic product of commuting zones	Bureau of Economic Analysis
INC	Income per capital of commuting zones	Bureau of Economic Analysis
TREND	The time trend index	

4.3.4 Instrument Variable: EU robot exposure

The following section introduces EU robot exposure as an instrument of comparison to U.S. robot exposure and the first-stage relationship between EU and US robot exposure. Given the issue of endogeneity caused by the independent variable (ROBOTUS) is correlated the error term and OLS coefficients are biased, a valid instrumental variable that satisfies the following requirements is needed:

1 Instrument relevance: the correlation between the instrumental variable and the endogenous variable should not be zero.

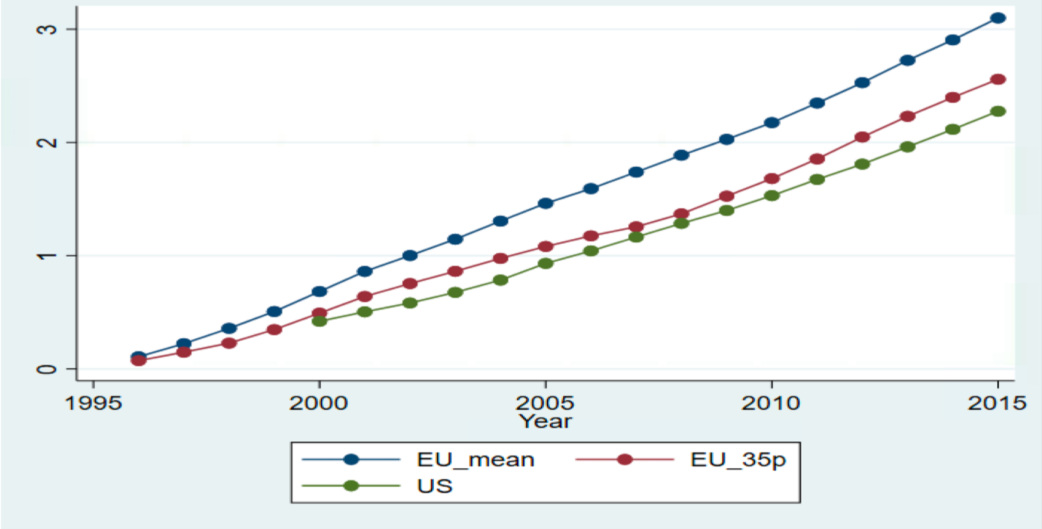
2 Instrument exogeneity: the correlation between the instrumental variable and the error term should be zero.

One important difference between these two requirements exist. Usually, it is impossible to check the exogeneity, and an assessment of economic behaviours is essential to maintain this hypothesis. Conversely, the relevance of an instrument is easier to check by running a regression between the endogenous variable and the instrumental variable. However, a small correlation between the instrumental variable and an endogenous regressor weakens the instrument, posing potential issues to the study by resulting in inconsistent estimations under the 2SLS model. Therefore, the relevance of the ROBOTUS instrument is assessed in relation to its validity.
The time plots of robots per worker can clearly show the development of robots within the chosen time period and can compare the trend between different countries. Figure4-2 plots the mean trend and the 35th percentile of industrial robots per thousand workers in selected EU countries, indicated by the blue and red line. Additionally, U.S. industrial robots per thousand workers is added in this figure (green line) as a point of comparison. For EU countries, the 35th percentile of robot density starts from near 0.5 robots per thousand workers in 2000 and increases to 2.5 robots per thousand workers in 2015. The average of EU robot density also shows the increasing trend from the early 2000s to 2010, with an evident higher value than the 35th percentile. Noticeably, robot density in the U.S. also gradually increases alongside the trend for EU countries but with lower values. The most important finding from Figure4-2 is the exact same trend between the U.S. robot density (the green line) and the 35th percentile EU robot density (the red line). Thus, this paper uses EU robot exposure as the proxy of U.S. robot exposure, constructed by the following equation:

$$ROBOTEU = \sum_{i \in \mathcal{I}} \ell_{ci,t} \left(p_{35} \left(\frac{R_{i,t+1}}{L_{i,t}} \right) - p_{35} \left(\frac{R_{i,t}}{L_{i,t}} \right) \right) \tag{19}$$

where $\ell_{ci,t}$ is still the share of employment of industry i in commuting zone c and $\left(p_{35}\left(\frac{R_{i,t+1}}{L_{i,t}}\right) - p_{35}\left(\frac{R_{i,t}}{L_{i,t}}\right)\right)$ shows the changes of the 35th percentile of EU industrial robots per thousand workers. Given the similarities and variation path between the U.S. and the 35th percentile curve in Figure4-2, the 35th percentile was selected.

Figure 4-2. Industrial robots per thousand workers in the United States and Europe



Notes: The blue line means the average of industrial robots per thousand workers in Europe; the red line represents the 35th percentile of industrial robots per thousand workers in Europe and the green line represents the industrial robots per thousand workers the United States).

Specifically, this paper analyses the correlation between EU and U.S. robot exposure at industry level. As outlined in FigureA4-1 in the appendix, robot exposure in EU and U.S. industries between 2000 and 2008 is portrayed by the top panel, whereas changes between 2000 and 2016 is portrayed in the bottom panel. For both panels, the vertical axis denotes the United States and the horizontal axis denotes EU countries. In terms of the top panel, industries that have increasing robot exposure within 2000 to 2008 also use more robots in the United States from 2000 to 2008. Additionally, the bottom panel demonstrates the similar relationship of robot exposure between the United States and EU countries from 2000 to 2016.
Furthermore, this analysis also draws upon the correlation table of the change in robot exposure at industry level between the United States and European countries for two periods (2000-2008 and 2000-2016).
FigureA4-2 in the appendix highlights the correlation between the change of U.S. and EU robot exposure at industry level between 2000 and 2008 is 0.973; the correlation between U.S.

and EU between 2000 and 2016 is 0.963. Evidently, both high correlation values demonstrate the "relevance" of the instrument.
For the first-stage relationship, which regresses the change of U.S. robot exposure with the exogenous change of robot exposure. The first-stage is applied in the instrumental variables as the following:

$$\sum_{i\in\mathcal{I}} \ell_{ci,t}\left(\frac{R^{US}_{i,t+1}}{L^{U,S}_{i,t}} - \frac{R^{US}_{i,t}}{L^{US}_{i,t}}\right) = \pi \sum_{i\in\mathcal{I}} \ell_{ci,t}\left(p_{35}\left(\frac{R_{i,t+1}}{L_{i,t}}\right) - p_{35}\left(\frac{R_{i,t}}{L_{i,t}}\right)\right) + \Gamma X_{c,t} + \nu_c \tag{20}$$

where $\Gamma X_{c,t}$ denotes a series of control variables and p35 means the 35th percentile.

4.4 Empirical specification and methodology

The following chapter outlines the estimation methods and regression model used in this study. To assess the impact of robot exposure on the number of "deaths of despair" in the U.S., three categories of mortality data are collected: "drug-induced causes", "alcohol-induced causes", and "other-induced causes". Importantly, however, the influence of other variables that may affect mortality rates and robot adoption, is noted. The general model used in the regression is as follows:

$$Y_{ct} = \beta ROBOTUS_{ct} + \Gamma X_{ct} + \theta_t + \epsilon_{ct} \tag{21}$$

where Y refers to different kinds of mortality and their first difference. Y includes mortality caused by drug ($DRUG_{ct}$), mortality caused by alcohol ($ALCOHOL_{ct}$), mortality caused by other factors ($OTHER_{ct}$), the change of mortality caused by drug ($cDRUG_{ct}$), the change of mortality caused by alcohol ($cALCOHOL_{ct}$) and the change of mortality caused by other factors ($cOTHER_{ct}$) of commuting zone c in year t in the United States; $ROBOTUS_{ct}$ represents the change of robot exposure in the United States of commuting zone c in year t. X_{ct} means a set of controls, which includes $CONSTRUCT_{ct}$ denotes commuting zones' employment of the construction sector, $MANUFACT_{ct}$ denotes commuting zones' employment of the manufacturing sector, $NONTRADE_{ct}$ refers to commuting zones' employment of the non-tradable sector, $IMPORTCN_{ct}$ indicates commuting zones' imports from China to the United States, GDP_{ct} shows commuting zone's gross domestic products, INC_{ct} signifies commuting zone's real income per capita, POP_{ct} indicates the total population of commuting zones, $WORKING_{ct}$ denotes the working-age population of commuting zones, $BLACK_{ct}$ represents the black population of commuting zones, $HISPANIC_{ct}$ signifies the Hispanics population of commuting zones and θ_t are year dummies. In this paper, there are six models used in the estimation; a detailed outline of each model is provided in the appendix section.

Figure4-3 and Figure4-4 provide preliminary evidence of the positive relationship between robot exposure and mortalities caused by "disease of despair". Figure4-4 demonstrates the scatter plot between robot exposure and drug-related mortalities of people at working age in the United States from 2000 to 2015. Additionally, the figure illustrates the scatter graph between robot exposure in the U.S. and mortalities caused by alcoholism; robot exposure appears to positively affect both drug-induced and alcohol-induced mortalities. Evidently, therefore, positive correlations are consistent with the hypothesis that increasing robot usage harms the mental health of workers and leads to despairing behaviors, such as consuming drugs and excessive drinking.

Figure 4-3. The scatter plot between the robot exposure and mortality caused by drug in the United States from 2000 to 2015

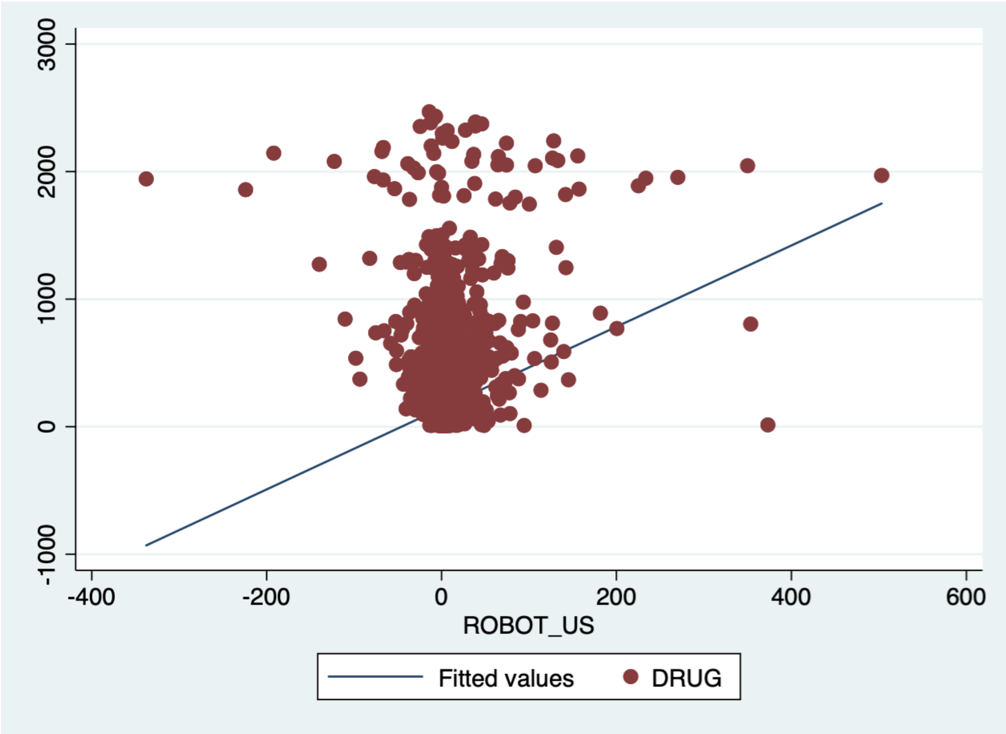
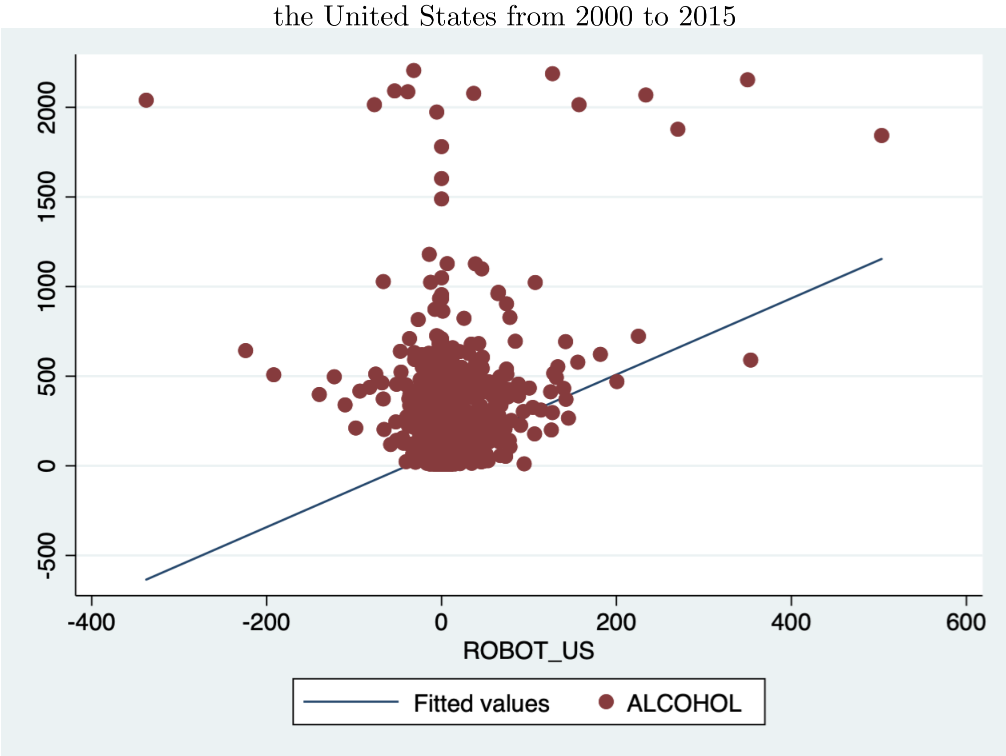


Figure 4-4. The scatter plot between the robot exposure and mortality caused by alcohol in the United States from 2000 to 2015



4.4.1 Two Stages Least Squares (2SLS)

Ordinary Least Sauqre (OLS) is applied as an estimation method of the study. Two-Stage least squares (2SLS) estimation is subsequently applied to deal with the potential endogeneity problem of robot exposure; endogeneity issues occur when residuals of the dependent variable are associated with independent variables. In this study, the error terms of mortality may correlate with ROBOTUS, thereby resulting in issues of endogeneity. The instrumental variable can be used to solve the problem of endogeneity by generating a new variable and replacing the endogenous variable. Notably, there are two requirements when selecting the instrumental variable. Firstly, the instrument variable should be correlated with the problematic variable. Secondly, the correlation between the instrumental variable and the error term should be zero, indicating the instrumental variable is not a direct cause of the dependent variable. Omitted variable bias is the main reason of why ROBOTUS might be endogenous; omitted variables may affect robot usage at industry level, and the effect of these omitted variables will be captured by the error term, leading to biased results. Thus, this paper constructs the instrument of U.S. robot exposure by using the robot exposure from eight European countries and the detailed process of creating the instrument is subsequently outlined in the following section.
In order to check the potential endogeneity of ROBOTUS, we apply the Durbin and Wu–Hausman tests after adding the instrumental variable into six regression models. One aim of the Huasman test is to appropriately select an effective estimation method from OLS and 2SLS. The null hypothesis of the Huasman test is that variables are exogenous, which means OLS coefficients are more efficient than 2SLS coefficients. Test results reject the null hypothesis for equation (27) to (32) and indicate that 2SLS provides the most preferred estimator. Noticeably, the OLS estimator may be biased due to endogeneity – a problem that may be corrected using the instrumental variable and 2SLS estimation. The GMM estimation could also be used to solve the endogeneity problem. It is more appropriate to use GMM estimation in the over-identified case, in which the number of instruments is greater than the number of endogenous variable. In this paper, we are in the just-identified case, thus 2SLS estimation is better.
The 2SLS estimation includes two regressions, one from the first stage and the other from the second stage. In the first stage, the endogenous variable (ROBOTUS) is regressed on the instrumental variable and all other exogenous variables to obtain the fitted value of ROBOTUS. In the second stage, we replace the ROBOTUS by using the fitted value of ROBOTUS from the first stage when running regressions of equation (21), to model (26). In the following section, we explain the detailed process of dealing with the issue of endogeneity. The main model that is going to be estimated is outlined below:

$$y = \beta_1 x + \beta_2 z + v \tag{22}$$

where y denotes the "DSA" mortality and x signifies the U.S. robot exposure, which is the endogenous independent variable, and z is the exogenous independent variable and υ refers to the error term. As ROBOTUS is correlated with the error term, the 2SLS model is used to solve this problem by replacing x with the fitted value of x. The predicted value of x can be obtained from the first stage regression with the instrumental variable:

$$x = \Gamma_1 \Phi + \Gamma_2 z + \mu \tag{23}$$

where x is the fitted value of ROBOTUS, ϕ is ROBUTEU as the instrument variable and z represents remaining independent variables that are exogenous. In the second stage regression, we replace the x in the original model by using the fitted value of ROBOTUS from the first stage and the new model can be expressed as:

$$y = \beta_1 x + \beta_2 z + \upsilon \tag{24}$$

where y is still the "DSA" mortality as dependent variable, x is the fitted value of ROBOTUS from the first stage and z is the rest of exogenous idependent variables.

4.4.2 Fixed effects model (FE) and Random effects model (RE)

There may exist some unobserved and fixed effects that affect the dependent variable and do not change over time. If these unobserved effects correlate with the independent variables, the OLS estimator will be biased and inconsistent. Thus, the fixed effect model may be used to eliminate the unobserved effects, enabling the unobserved effects to be correlated with the independent variables. The fixed effects regression model can be expressed as follows:

$$y_{it} = \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta kxitk + a_i + u_{it} \tag{25}$$

with i=1,...,n and t=1,...,T. a_i are entity-specific intercepts that capture heterogeneities across entities. Y denotes the mortality, x represents a series of independent variables, u_{it} signifies the error term. The aim of the fixed effects model is to remove a_i. The main difference between FE model and RE model is that RE model assumes the correlation between the unobserved effect and independent variables is zero. The random effects model shows as the following:

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta k x_{itk} + a_i + u_{it} \tag{26}$$

where a_i captures the unobserved effects, it is not correlated with any independent variables in the random effects model. Under this assumption of a_i, the RE estimation will be more efficient than FE estimation. Because the fixed effects display a correlation between the unobserved effect and independent variables but the random effects does not allow, the FE model is considered more suited to this study. Additionally, the Hausman test provides evidence to determine whether the FE or RE model is more efficient. The null hypothesis of the Hausman test is that the coefficient of random effects estimator is the same as the consistent fixed effect estimator. Results of the Huasman test by using different mortalities as the dependent variable reject the null hypothesis. In other words, the fixed effects model is more efficient than the random effects. We add both time fixed effects and cross-sectional fixed effects in the following regressions.

4.5 Empirical results

The following section presents the regression results of six models under different estimation methods. As previously stated, only data collected from the working population in the United States is analysed in this study, as people who are working are more likely to be affected by shocks from the job environment.

Table4-2 summarises the main regression results for the sample under different estimation methods. All of the estimated coefficients can be interpreted as the change of commuting zone level mortality due to variations over time in U.S. robot exposure or to other explanatory variables. The column number differs from different dependent variables in equation (10) to equation (15). The full OLS and IV estimation results are portrayed in TableA4-1 and TableA4-2 in the appendix.

Panel A shows the regression result under the OLS estimation. Column (1) indicates that the changes in robot exposure negatively affects drug-related mortalities at a 1 percent significance level. Crucially, one additional robot per thousand workers reduces the death of 775 people caused by drug. In column (3), however, one robot per thousand workers reduced the number of alcohol related fatalities by 198 people; thus having a negative effect at a 1 percent significance level. Evidently, in column (5) and (6), changes in robot exposure have both a negative and significant effect on the other-caused mortality category; a 5 percent and 1 percent significance level respectively. Noticeably, mortalities caused by drug abuse is the variable that is most heavily affected by robot exposure compared to other related causes. We can see the adjusted R-squared for drug-caused mortality, alcohol-caused mortality and other-caused mortality are relatively high, which means the explanatory power for these three model are higher than models with their first difference.

In essence, the negative influence of robot exposures on mortalities caused by drug abuse, alcoholism, or other factors, implies that increased robot usage leads to declining “deaths of despair”; a finding which differs from existing literature. As such, the findings of this study suggest that people may not experience higher pressure from increasing robot penetration in their lives, or indeed, their mental health may even improve. As explained in section 3, this negative effect under OLS may be biased due to omitted variables that will inevitably affect the exposure of robots and mortality rates simultaneously. In addition

Panel B provides regression results under the fixed effects estimation, which captures the unobserved fixed effect. In column (2), robot exposure affects the change in drug-induced mortalities positively and significantly at 5 percent. This impact indicates that drug-related mortalities will increase as robot exposure increases, though the effect of robot exposure on the change in alcohol-induced and other-induced mortalities remains negative. Negative effects on the number of fatalities was not expected. It is feasible to suggest that potential endogeneity caused this negative effect; although we controlled the unobserved fixed effects, omitted variables that cause biased results may still exist. Accordingly, the 2SLS model is used in the next stage to correct the endogeneity problem and improve the estimation result.

Panel C includes all regressions using the 2SLS estimation method with fixed effects, which is the most appropriate method as it solves the possible endogeneity of ROBOTUS given the influence of omitted variables. Robot exposure in the United States is instrumented by robot exposure in Denmark, Finland, France, Germany, Italy, Sweden, the United Kingdom, and Spain. Thus, external influences inevitably impact the results of the regression analysis and the significance of the coefficients of the instrument. Starting with the regression of column (2), the U.S. robot exposure has a positive and significant effect on the change in drug-related mortalities (cDRUG), at a 1 percent significance level. One additional robot per thousand workers increases drug-related deaths of 3049 people between two years. As such, drug-related mortalities in the current year has increased compared to last year when robot usage was higher. The instrumented robot usage also displays positive and significant effects on alcohol-caused mortalities in column (3) and column (4) at 1 percent and 5 percent significance levels. One additional robot per thousand workers increases the number of deaths caused by drinking alcohol by 1355 people. In column (5), mortalities caused by other factors is affected by robot exposure positively and significantly at a 1 percent significance level. The change in other-caused mortalities is observed to increase by 11030 deaths for each additional robot per thousand workers. In addition, the coefficient value of instrumented robot exposure on the change in other-induced mortalities is much higher than in other columns. One possible explanation for these positive effects is that people may be fearful that higher robot penetration will reduce their wage, or replace their job. This kind of fear can develop into mental health issues caused by pressure, stress, and anxiety; feeling like there is no other place to turn, people may turn to drugs and alcohol in their efforts to escape their suffering. In addition, the within R-squared for drug-caused mortality, alcohol-caused mortality and other-caused mortality still higher than models with their first difference, which suggests the higher explanatory power.

There is strong evidence supporting the correlation between poverty, unemployment, and the prevalence of opioid consumption. Moreover, higher prescription of opioid is more likely to occur in counties with worse economic conditions; for example, rural areas have higher drug overdose mortalities compared to urban areas (Ghertner and Groves, 2018). Aliprantis et al. (2019) also state that the increase of local opioid prescription rates correlates to a decrease in the prime age of labour force participation for both men and women.

Nevertheless, long-term labor market fluctuations are likely to explain the rising share of individuals who misuse prescription opioids compared to short-term fluctuation. These evidence all support our finding that the drug-caused mortality will increase due to the growing robot usage, deteriorating labor market and worse mental health. Similar to drug related deaths, deaths caused by alcoholism are also impacted by increased robot exposure. The findings of this study support those presented by Abeliansky and Beulmann (2019), who state increasing robot usage will inevitably result in a larger deterioration of mental health among individuals. Accordingly, their results are represented by generating a mental health index from survey questions related to interviewee's mental health in Germany.

The coefficient of instrumented robot exposure is both positive and significant on mortalities caused by all other factors except drug and alcoholism. Notably, this finding is consistent with the noticeable decline in mortalities of middle-aged people in the United States. Accordingly, it is possible to suggest that the increased exposure of industrial robots leads to decreasing employment and lower incomes for workers (Acemoglu and Restrepo, 2017). Evidently, therefore, the economic status of workers deteriorates as they have less disposable income; some individuals may no longer be able to afford health care as their health worsens. Furthermore, individuals from lower-income households and without health insurance are more likely to misuse opioids; increased poverty and an reduced job vacancies may worsen the situation of inequal access to health care and treatment resources (Ghertner and Groves, 2018). Moreover, a number of studies note the benefits of increased minimum wage on the overall health of individuals. As robots are increasingly used in industry, the labor market environment will undoubtedly be adversely affected, reducing job prospects and opportunities and impacting the health of individuals.

Table 4-2. Baseline regression results of robot exposure and mortality

Dependent Variable: Mortality caused by different factors						
	Panel A: OLS estimation					
	(1)	(2)	(3)	(4)	(5)	(6)
	DRUG	cDRUG	ALCOHOL	cALCOHOL	OTHER	cOTHER
U.S. robot exposure (ROBOTUS)	-775.0***	47.95	-198.2***	-172.2***	-531.0*	-613.2***
	(-5.02)	(0.68)	(-3.46)	(-5.66)	(-2.11)	(-7.49)
	Panel B: Fixed effects estimation					
	(1)	(2)	(3)	(4)	(5)	(6)
	DRUG	cDRUG	ALCOHOL	cALCOHOL	OTHER	cOTHER
U.S. robot exposure (ROBOTUS)	-17.71	173.6*	-11.01	-184.4***	-61.14	-224.8*
	(-0.19)	(2.07)	(-0.37)	(-5.11)	(-0.84)	(-2.55)
	Panel C: 2SLS estimation					
	(1)	(2)	(3)	(4)	(5)	(6)
	DRUG	cDRUG	ALCOHOL	cALCOHOL	OTHER	cOTHER
U.S. robot exposure (ROBOTUS)	1268.7	3049.3**	1355.2**	1171.8*	-75.52	11029.4***
	(1.31)	(2.70)	(2.96)	(2.35)	(-0.10)	(4.78)
Demographic controls	✓	✓	✓	✓	✓	✓
Sector controls	✓	✓	✓	✓	✓	✓
Economic controls	✓	✓	✓	✓	✓	✓

Notes: The table summarizes OLS, FE and IV estimates of regressions between the U.S. robot exposure and the U.S. mortality caused by different factors. All regressions use the panel data from 2000 to 2015 at the U.S. commuting zone level. Each panel shows different estimation methods. Each column presents different dependent variable (Total drug-induced mortality, the change in drug-induced mortality, total alcohol-induced mortality, the change in alcohol-induced mortality, total other-induced mortality and the change in other-induced mortality). The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).Exogenous instruments in panel B are the robot exposure of eight European countries.

4.6 Robustness check

The following section details the process in which the results of the regression analysis are tested for their robustness. Table4-3 contains the regression results for all robustness checks. All results under different robustness checks are consistent with the baseline result, reinforcing robots' positive effect on drug-related, alcohol-related and other-related mortalities. For brevity, the analysis only interprets the estimation result under the 2SLS model.

As illustrated in FigureA4-1, with over 19 industries, the automobile industry utilises the highest number of robots. All regressions in panel A construct the robot exposure by excluding robot usage in the automotive sector from the study; thus, previous baseline results are not driven by this industry.

Starting with column (2) in panel A, the coefficient of instrumented robot exposure still shows positive and significant sign on the change of drug-caused mortality (cDRUG) at 5 percent significance level under the 2SLS estimation. One additional robot per thousand workers increase the death caused by drug of 3049 individuals between two years. In column (3) and

(4), the alcohol-induced mortality and the change in alcohol-induced mortality are positively and significantly affected by the instrumented robot exposure at 1 percent and 5 percent significance level. It can be seen that one robot per thousand workers leads to the increase in deaths caused by alcohol of 1355 people. In column (6), the robot exposure still affect the other-caused mortality (OTHER) positively and significantly at 1 percent significance level. These results are consistent with the baseline regression results; higher robot density has a negative and robust effect on peoples' mental health. Accordingly, the results of this study did not change after excluding the effect of the automobile industry from our outcomes. In addition, the effect of robot usage on mortality rates is not driven by one specific industry or sector.

In panel B, all regressions use the data of the sub-period from 2006 to 2014 to prove that the effect of robots on fatalities does not only occur in specific periods. Notably, if a positive relationship between robot exposure and DSA deaths exists in the sub-periods, we can assume the previous baseline result is robust. The sub-period used in the robustness test includes periods used across the baseline test. The instrumented robot exposure still displays a positive and significant effect on drug-related mortalities (DRUG) at a 1 percent significance level in column (1) panel B. One new robot per thousand workers increase deaths caused by drug of 1639 people. For the change of drug-caused mortality (cDRUG) in column (2), the coefficient of instrumented robot exposure is also positive and significant at 5 percent significance level. In column (3), the robot exposure affects the alcohol-caused mortality (ALCOHOL) positively and significantly at 5 percent significance level. One additional robot per thousand workers leads to the increase of alcohol-induced deaths of 792 individuals. In column (5) and (6), mortality caused by other factors and the change in other-cause mortality are affected by the instrumented robot exposure positively and significantly at 1 percent significance level. Noticeably, therefore, the estimated result using sub-period samples is consistent with the baseline result. Though less observations are used in this robustness check, the result still indicates that increasing use of robots will subsequently harm the mental health of workers, which is reflected in rising DSA fatalities.

In panel C, all models take the change of main independent variables over time into consideration by adding the time trend index (TREND) into the regression. Some trends that may associate with independent variables and the dependent variable simultaneously, the potential problem is the spurious regression problem if the estimation ignores this possibility. The time trend index is used to capture the effect from time trend and we generate the index by assigning a number to each year that increases year by year. For instance, the value of this time trend index is equal to 1 for all commuting zones in 2000, equal to 2 in 2001, and equal to 16 in 2015.

After adding the time trend index, the regression results under the IV estimation proves that the baseline result is robust. Evidently, instrumented robot exposure has a positive and significant effect on the change in drug-induced deaths at 5 percent significance level in column (2). One additional robot per thousand workers increases the death caused by drug of 3049 people between two years. Turning to column (3) and column (4), alcohol-induced mortalities are influenced by robot exposure positively and significantly at 5 percent and 1 percent significance level. One new robot per thousand workers leads to the increase in alcohol-caused deaths of 1355 individuals. In column (6), the change in mortalities caused by all other factors are affected by the instrumented robot exposure significantly at 1 percent level; one additional robot per thousand workers increases deaths caused by all other factors of 11030 people between two years. The instrumented robot exposure still shows a positive and significant effect on the change in drug-related and alcohol related mortalities, and changes in other causes of mortalities. These results are consistent with the baseline results after we note the time trend effect.

Table 4-3. Robot exposure and mortality, robustness check

Dependent Variable: Mortality caused by different factors						
	Panel A: Excluding the automotive industry					
	(1)	(2)	(3)	(4)	(5)	(6)
	DRUG	cDRUG	ALCOHOL	cALCOHOL	OTHER	cOTHER
U.S. robot exposure (ROBOTUS)	1268.7	3049.3**	1355.2**	1171.8*	-75.52	11029.5***
	(1.31)	(2.70)	(2.96)	(2.35)	(-0.10)	(4.78)
	Panel B: Using sub-periods from 2006 to 2016					
	(1)	(2)	(3)	(4)	(5)	(6)
	DRUG	cDRUG	ALCOHOL	cALCOHOL	OTHER	cOTHER
U.S. robot exposure (ROBOTUS)	1639.3**	2060.9*	792.2*	223.6	1119.7**	1838.0**
	(2.36)	(2.84)	(2.86)	(0.68)	(2.17)	(2.28)
	Panel C: Adding the time trend index					
	(1)	(2)	(3)	(4)	(5)	(6)
	DRUG	cDRUG	ALCOHOL	cALCOHOL	OTHER	cOTHER
U.S. robot exposure (ROBOTUS)	1268.7	3049.3**	1355.2**	1171.8*	-75.52	11029.5***
	(1.31)	(2.70)	(2.96)	(2.35)	(-0.10)	(4.78)
Demographic controls	✓	✓	✓	✓	✓	✓
Sector controls	✓	✓	✓	✓	✓	✓
Economic controls	✓	✓	✓	✓	✓	✓

Notes: The table summarizes IV estimation results between the U.S. robot exposure and the U.S. mortality caused by different factors under different specifications for the robustness check. Exogenous instruments in panel B are the robot exposure of eight European countries. All regressions use the panel data at the U.S. commuting zone level. Each panel represents different measures or specifications. Each column presents different dependent variable (Total drug-induced mortality, the change in drug-induced mortality, total alcohol-induced mortality, the change in alcohol-induced mortality, total other-induced mortality and the change in other-induced mortality). The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).

Moreover, Figure4-3 and Figure4-4 suggest the existence of outliers that may drive the results. Most of the outliers come from the commuting zone 38300. After we drop the data from this commuting zone, robot exposure still has positive and significant effect on alcohol-caused mortality and other-caused mortality. In other words, the previous results are robust and not driven by the outliers. In addition, most of counties in this commuting zone comes from California, which is one of the state that has highest robot stock in the United States and these robots are mainly applied in the automotive sector. Like we discussed in this robustness check section, the previous baseline result is robust after we exclude the robot exposure in the automotive sector based on Table4-3.

4.7 Discussion

The previous analysis shows that robot usage has a significant impact on workers' mental health. Upon conducting a series of robustness checks, it is apparent that the positive effect that industrial robots have on the number of deaths caused by drugs, alcohol, and other factors, as indicated by the baseline result in Table4-2, is robust. Thus, the baseline result indicates that the increasing usage of industrial robots has the potential to negatively impact the mental health of workers.

Due to the possible endogenous variable, the U.S. robot exposure, the OLS estimator is arguably biased. To mitigate this, this research utilises an instrumental variable, namely robot exposure in European countries, to solve the problem of endogeneity and produce unbiased estimation results. Furthermore, this study looks to provide an unparalleled and fresh perspective on the impact that industrial robots have on the mental health of individuals in the United States. Nevertheless, there also exist limitations to this study that may require improvements to be made. Firstly, the transmission channel between the industrial robot usage and the mental health outcome is not clearly identified in this study. According to previous studies, this paper assumes the underlying channel that links the industrial robot and mental health is the labour market. In other words, robot exposure affects the mental health of individuals through the variations in labour environment indicators, such as employment and income. However, this assumption is unsupported by empirical evidence as there is no data available to represent the stress of workers from job uncertainties at a commuting zone level.

Secondly, this paper only uses the mortality caused by drug and alcohol to represent the mental health outcome. Results will be more representative if different indicators of mental health are applied in the estimation as alternatives of "DSA" fatalities; for example, counseling related to mental health, therapy of mental problems, and questionnaires that focus on the mental state of individuals. However, due to the current lack of data availability, with regard to the aforementioned variables, these options could be used as future extensions of the model.

Furthermore, findings from this paper could also aid in future policy making. The negative effect of industrial robots on the mental health of workers indicates the increasing association between robots and individuals, and therefore indicates that more scrutiny is needed to deal with this problem. Considering the possible societal repercussions, policymakers should be more cautious when introducing new technologies, such as artificial intelligence and robots. Previous research and data indicate that changes in technology have the potential to improve the welfare of some and deteriorate the welfare of others. Therefore, it is vital that policies that could have an impact on the future of individuals should work in conjunction with the private sector to consider measures that protect the mental health of those who are vulnerable. Companies should also take the mental health of their employees into consideration when adopting new technologies or increasing the use of existing technologies.

4.8 Conclusion

The rapid development of labour-replacing technologies, such as artificial intelligence and robotics, is a highly contentious topic. Increasingly, scholars have investigated the relationship between these technologies and employment, and the possibility of replacing human labour with robots. The United States, in particular, have been noted to suffer from negative shocks in employment and wage from the increasing usage of industrial robots (Acemoglu and Restrepo, 2017). This stipulates that the increasing use of robots has a negative effect on the mental health of people. An individual's stress level may increase due to the fear of losing their jobs or because of a decrease in their wages. decreasing wages as the increasing usage of robots.

This paper analyses existing evidence to conclude that robots do influence the mental health of people at working age by using "deaths of despair" as a proxy to measure the variation of people's mental health. Accordingly, it can be seen that the mental health of people (20 to 59 years old) deteriorates when experiencing higher robot exposure, as indicated by the increasing mortality caused by drug, alcohol, and other factors. The pressure from robots on workers is reflected in worries about decreasing wage and fewer job opportunities. This kind of stress may lead workers to take extreme and negative actions, such as drug and alcohol abuse; therefore, increasing drug and alcohol related deaths. The results also show that an increase in robot usage leads to the increase in mortality caused by all other factors (excepting drug and alcohol), thereby having adverse effects on the general health of workers. The negative impact that lower wages and the lack of job stability has on the labour market also suggests that individuals will have less disposable income to spend on their physical and mental health, therefore potentially causing a decline in their health. Different robustness checks show these results are robust. The current literature lacks data stipulating the impact of these automation technologies on the health of people. As such, this paper looks to build on the existing literature by providing evidence of robots' effect on the mental health of individuals at working age in the United States. The lack of job security is likely to harm the mental health of workers and reduce the efficiency of their work. Thus, it is in the best interests of companies to consider the mental health of their employees when introducing new technologies in the workplace. Every time when a new technology comes out, there are victims and winners. In other words, any progress in technologies brings improving welfare of some people and deteriorating welfare of other people. Therefore, policy-makers should think about how to protect workers when they experience the shock from new technologies. Although this research primarily focuses on the United States, the findings can also be used as a point of reference for other countries as the development of AI and robots is inevitable in the future.

4.9 Appendix

4.9.1 Explanation of models in regression

In this part of the appendix, we are going to look at different equations that are shown in the main text. These equations differ in the left-hand side and keep same in the right-hand side. For the first three models, the explained variable is mortality that caused by drug, alcohol and other factors ($DRUG_{ct}$, $ALCOHOL_{ct}$, $OTHER_{ct}$) respectively in the United States of commuting zone c and measured in year t. In addition, the effect of robot exposure on the changes of mortality caused by drug, alcohol and other factors ($cDRUG_{ct}$, $cALCOHOL_{ct}$, $cOTHER_{ct}$) at U.S. commuting zone level are also examined in the last three models. Remaining independent variables are same in these six models, where where $ROBOTUS_{ct}$ signifies the change of robot exposure at the U.S. commuting zone level, $CONSTRUCT_{ct}$ denotes commuting zones' employment of the construction sector, $MANUFACT_{ct}$ denotes commuting zones' employment of the manufacturing sector, $NONTRADE_{ct}$ refers to commuting zones' employment of the non-tradable sector, $IMPORTCN_{ct}$ indicates commuting zones' imports from China to the United States, GDP_{ct} shows commuting zone's gross domestic products, INC_{ct} signifies commuting zone's real income per capita, POP_{ct} indicates the total population of commuting zones, $WORKING_{ct}$ denotes the working-age population of commuting zones, $BLACK_{ct}$ represents the black population of commuting zones, $HISPANIC_{ct}$ signifies the Hispanics population of commuting zones, $EDUC1_{ct}$ refers to the share of adults with less than a high school diploma, $EDUC2_{ct}$ shows the share of adults with a high school diploma, $EDUC3_{ct}$ signifies the share of adults with a bachelor's degree or higher degree and θ_t are year dummies.

$$\begin{aligned} DRUG_{ct} = \beta_c + \beta_{1ct}ROBOTUS_{ct} + \beta_{2ct}CONSTRUCT_{ct} + \beta_{3ct}MANUFACT_{ct} \\ +\beta_{4ct}NONTRADE_{ct} + \beta_{5ct}IMPORTCN_{ct} + \beta_{6ct}GDP_{ct} + \beta_{7ct}INC_{ct} + \beta_{8ct}POP_{ct} \\ +\beta_{9ct}WORKING_{ct} + \beta_{10ct}BLACK_{ct} + \beta_{11ct}HISPANIC_{ct} + \beta_{12ct}EDUC1_{ct} \\ +\beta_{13ct}EDUC2_{ct} + \beta_{14ct}EDUC3_{ct} + \theta_t + \epsilon_{ct} \end{aligned} \tag{27}$$

$$\begin{aligned} cDRUG_{ct} = \beta_c + \beta_{1ct}ROBOTUS_{ct} + \beta_{2ct}CONSTRUCT_{ct} + \beta_{3ct}MANUFACT_{ct} \\ +\beta_{4ct}NONTRADE_{ct} + \beta_{5ct}IMPORTCN_{ct} + \beta_{6ct}GDP_{ct} + \beta_{7ct}INC_{ct} + \beta_{8ct}POP_{ct} \\ +\beta_{9ct}WORKING_{ct} + \beta_{10ct}BLACK_{ct} + \beta_{11ct}HISPANIC_{ct} + \beta_{12ct}EDUC1_{ct} \\ +\beta_{13ct}EDUC2_{ct} + \beta_{14ct}EDUC3_{ct} + \theta_t + \epsilon_{ct} \end{aligned} \tag{28}$$

$$
\begin{aligned}
ALCOHOL_{ct} = \beta_c + \beta_{1ct}ROBOTUS_{ct} + \beta_{2ct}CONSTRUCT_{ct} + \beta_{3ct}MANUFACT_{ct} \\
+\beta_{4ct}NONTRADE_{ct} + \beta_{5ct}IMPORTCN_{ct} + \beta_{6ct}GDP_{ct} + \beta_{7ct}INC_{ct} + \beta_{8ct}POP_{ct} \\
+\beta_{9ct}WORKING_{ct} + \beta_{10ct}BLACK_{ct} + \beta_{11ct}HISPANIC_{ct} + \beta_{12ct}EDUC1_{ct} \\
+\beta_{13ct}EDUC2_{ct} + \beta_{14ct}EDUC3_{ct} + \theta_t + \epsilon_{ct}
\end{aligned}
\tag{29}
$$

$$
\begin{aligned}
cALCOHOL_{ct} = \beta_c + \beta_{1ct}ROBOTUS_{ct} + \beta_{2ct}CONSTRUCT_{ct} + \beta_{3ct}MANUFACT_{ct} \\
+\beta_{4ct}NONTRADE_{ct} + \beta_{5ct}IMPORTCN_{ct} + \beta_{6ct}GDP_{ct} + \beta_{7ct}INC_{ct} + \beta_{8ct}POP_{ct} \\
+\beta_{9ct}WORKING_{ct} + \beta_{10ct}BLACK_{ct} + \beta_{11ct}HISPANIC_{ct} + \beta_{12ct}EDUC1_{ct} \\
+\beta_{13ct}EDUC2_{ct} + \beta_{14ct}EDUC3_{ct} + \theta_t + \epsilon_{ct}
\end{aligned}
\tag{30}
$$

$$
\begin{aligned}
OTHER_{ct} = \beta_c + \beta_{1ct}ROBOTUS_{ct} + \beta_{2ct}CONSTRUCT_{ct} + \beta_{3ct}MANUFACT_{ct} \\
+\beta_{4ct}NONTRADE_{ct} + \beta_{5ct}IMPORTCN_{ct} + \beta_{6ct}GDP_{ct} + \beta_{7ct}INC_{ct} + \beta_{8ct}POP_{ct} \\
+\beta_{9ct}WORKING_{ct} + \beta_{10ct}BLACK_{ct} + \beta_{11ct}HISPANIC_{ct} + \beta_{12ct}EDUC1_{ct} \\
+\beta_{13ct}EDUC2_{ct} + \beta_{14ct}EDUC3_{ct} + \theta_t + \epsilon_{ct}
\end{aligned}
\tag{31}
$$

$$
\begin{aligned}
cOTHER_{ct} = \beta_c + \beta_{1ct}ROBOTUS_{ct} + \beta_{2ct}CONSTRUCT_{ct} + \beta_{3ct}MANUFACT_{ct} \\
+\beta_{4ct}NONTRADE_{ct} + \beta_{5ct}IMPORTCN_{ct} + \beta_{6ct}GDP_{ct} + \beta_{7ct}INC_{ct} + \beta_{8ct}POP_{ct} \\
+\beta_{9ct}WORKING_{ct} + \beta_{10ct}BLACK_{ct} + \beta_{11ct}HISPANIC_{ct} + \beta_{12ct}EDUC1_{ct} \\
+\beta_{13ct}EDUC2_{ct} + \beta_{14ct}EDUC3_{ct} + \theta_t + \epsilon_{ct}
\end{aligned}
\tag{32}
$$

4.9.2 Tables and Figures

In this section of the appendix, we are going to displaying tables that show regression results between robot exposure and different types of mortality under different estimation methods. The first table presents OLS estimation results between the U.S. robot exposure and the U.S. mortality caused by different factors. All regressions use the panel data at the U.S. commuting zone level. Each column presents different dependent variable (Total drug-induced mortality, the change in drug-induced mortality, total alcohol-induced mortality, the change in alcohol-induced mortality, total other-induced mortality and the change in other-induced mortality).

Table A4-1. Full baseline regression results of robot exposure and mortality under OLS estimation

	OLS estimates for the effect of robot exposure on mortality caused by drug, alcohol anf other factors					
	DRUG	cDRUG	ALCOHOL	cALCOHOL	OTHER	cOTHER
U.S. robot exposure	-775.0***	47.95	-198.2***	-172.2***	-531.0*	-613.2***
	(-5.02)	(0.68)	(-3.46)	(-5.66)	(-2.11)	(-7.49)
Total population	44.09	71.33**	40.26*	-22.78*	2109.5***	77.69**
	(0.83)	(2.88)	(2.07)	(-2.15)	(23.99)	(2.67)
Working age population	442.3***	26.60	170.4***	25.49**	460.7***	34.10
	(10.27)	(1.33)	(10.84)	(2.99)	(6.47)	(1.44)
Black population	-257.2***	-102.3***	-229.4***	-30.95***	701.5***	-173.5***
	(-9.33)	(-7.80)	(-22.60)	(-5.48)	(15.66)	(-11.38)
Hispanics population	-323.5***	-60.13***	22.50***	-10.37***	-536.6***	-63.87***
	(-25.60)	(-10.31)	(4.79)	(-4.07)	(-27.05)	(-9.82)
Imports from China to the U.S.	-0.0108	0.00668	-0.00328	0.00193	-0.0280	-0.00294
	(-0.54)	(0.69)	(-0.33)	(0.35)	(-1.03)	(-0.33)
Employment of construction industry	-1718.6***	-147.9	445.5***	206.2**	3324.9***	855.5***
	(-4.97)	(-0.91)	(3.50)	(2.96)	(5.81)	(4.47)
Employment of manufacturing industry	-964.1***	-330.7***	-296.3***	-53.17*	1195.7**	87.17
	(-7.95)	(-5.47)	(-6.65)	(-2.05)	(6.06)	(1.23)
Employment of non-tradable industry	155.2	55.96	-107.4	-95.24*	-622.2	-352.3***
	(0.80)	(0.62)	(-1.5)	(-2.46)	(-1.96)	(-3.35)
Share of adults with less than a high school diploma	-2.509***	0.165	-2.008***	-0.137	0.589	0.360
	(-3.84)	(0.51)	(-6.92)	(-0.82)	(0.77)	(1.39)
Share of adults with a high school diploma	-4.382***	0.302	-3.600***	-0.409*	-3.187***	-0.255
	(-6.11)	(0.87)	(-11.72)	(-2.31)	(-3.43)	(-0.82)
Share of adults with a bachelor's degree or higher	-4.207***	-0.475	-2.691***	-0.400	-9.107**	-0.254
	(-4.04)	(-0.93)	(-6.07)	(-1.58)	(-7.24)	(-0.61)
Real gross domestic product	0.843***	-0.163	-0.0500	0.121**	-4.195***	-0.724***
	(7.18)	(-1.65)	(-1.18)	(2.86)	(-23.43)	(-6.42)
Income per capital	-2623.7***	461.4	-210.2	235.9	-2216.5**	283.5
	(-3.52)	(1.24)	(-0.66)	(1.27)	(-2.92)	(1.10)
Year dummies	✔	✔	✔	✔	✔	✔
Observations	2150	1832	1571	1519	3763	3441
Adjusted R-squared	0.8319	0.103	0.947	0.0767	0.9858	0.1802

Notes: The coefficients with *** are significant at the 0.1 percent confidence level (p<0.001); with ** are significant at the 1 percent confidence level(p<0.01); and with * are significant at the 5 percent confidence level(p<0.05).

The second table presents FE estimation results between the U.S. robot exposure and the U.S. mortality caused by different factors. All regressions use the panel data at the U.S. commuting zone level. Each column presents different dependent variable (Total drug-induced mortality, the change in drug-induced mortality, total alcohol-induced mortality, the change in alcohol-induced mortality, total other-induced mortality and the change in other-induced mortality).

Table A4-2. Full baseline regression results of robot exposure and mortality under FE estimation

	FE estimates for the effect of robot exposure on mortality caused by drug, alcohol anf other factors					
	DRUG	cDRUG	ALCOHOL	cALCOHOL	OTHER	cOTHER
U.S. robot exposure	-17.71	173.6*	-11.01	-184.4***	-61.14	-224.8*
	(-0.19)	(2.07)	(-0.37)	(-5.11)	(-0.84)	(-2.55)
Total population	415.00***	-56.53	285.0***	55.22	2602.0***	-763.6***
	(5.59)	(-0.67)	(11.93)	(1.54)	(44.80)	(-8.73)
Working age population	4161.2***	-253.3	889.2***	13.95	1847.2***	-1201.0***
	(21.22)	(-1.14)	(13.90)	(0.15)	(12.79)	(-5.42)
Black population	-1604.6***	-133.3	-1184.0***	483.0***	-8048.1***	4015.4***
	(-5.28)	(-0.45)	(-12.03)	(3.83)	(34.12)	(12.93)
Hispanics population	-1097.0***	4.868	-98.00***	9.859	-1314.3***	-75.95
	(-23.85)	(0.11)	(-6.55)	(0.52)	(-38.40)	(-1.71)
Imports from China to the U.S.	-0.00991	-0.00320	-0.000744	0.00128	-0.00558	0.00903
	(-0.73)	(-0.25)	(-0.13)	(0.18)	(-0.69)	(0.92)
Employment of construction industry	-677.2*	-242.1	315.9**	781.5***	5999.5***	-1461.6***
	(-2.01)	(-0.72)	(2.90)	(5.45)	(22.86)	(-4.17)
Employment of manufacturing industry	551.1	115.3	218.6*	-150.2	-2615.8***	1821.5***
	(1.66)	(0.35)	(2.02)	(-1.06)	(-10.20_	(5.35)
Employment of non-tradable industry	201.5	-59.49	-31.86	-167.3**	-797.9***	-664.3***
	(1.53)	(-0.50)	(-0.74)	(-3.29)	(-7.73)	(-5.33)
Share of adults with less than a high school diploma	-12.48**	-16.67***	1.364	-2.743	-5.831**	0.154
	(-2.84)	(-3.54)	(0.88)	(-1.23)	(-3.10)	(0.06)
Share of adults with a high school diploma	-16.62***	-15.54**	0.0289	-1.987	0.251	-1.486
	(-3.57)	(-3.09)	(0.02)	9-0.84)	(0.13)	(-0.53)
Share of adults with a bachelor's degree or higher	-18.69***	-7.454	-3.216	-1.032	-5.370*	0.0828
	(-3.84)	(-1.48)	(-1.91)	(-0.45)	(-2.28)	(0.03)
Real gross domestic product	-0.871***	1.550**	-0.234***	-0.268	-0.727***	3.035***
	(-8.22)	(3.22)	(-6.90)	(-1.30)	(-8.98)	(6.01)
Income per capital	-5218.1***	-1322.8	-697.0	478.4	-2015.7***	-392.5
	(-4.56)	(-1.13)	(-1.56)	(0.80)	(-4.67)	(-0.71)
Time fixed effect and commuting zone's fixed effect	✔	✔	✔	✔	✔	✔
Observations	2150	1832	1571	1519	3763	3441
Within R-squared	0.6985	0.0549	0.5638	0.12	0.7299	0.1980

Notes: The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).

The third table presents IV estimates of regressions between the U.S. robot exposure and the U.S. mortality. All regressions use the panel data from 2000 to 2015 at the U.S. commuting zone level. Each column presents different dependent variable (Total drug-induced mortality, the change in drug-induced mortality, total alcohol-induced mortality, the change in alcohol-induced mortality, total other-induced mortality and the change in other-induced mortality).

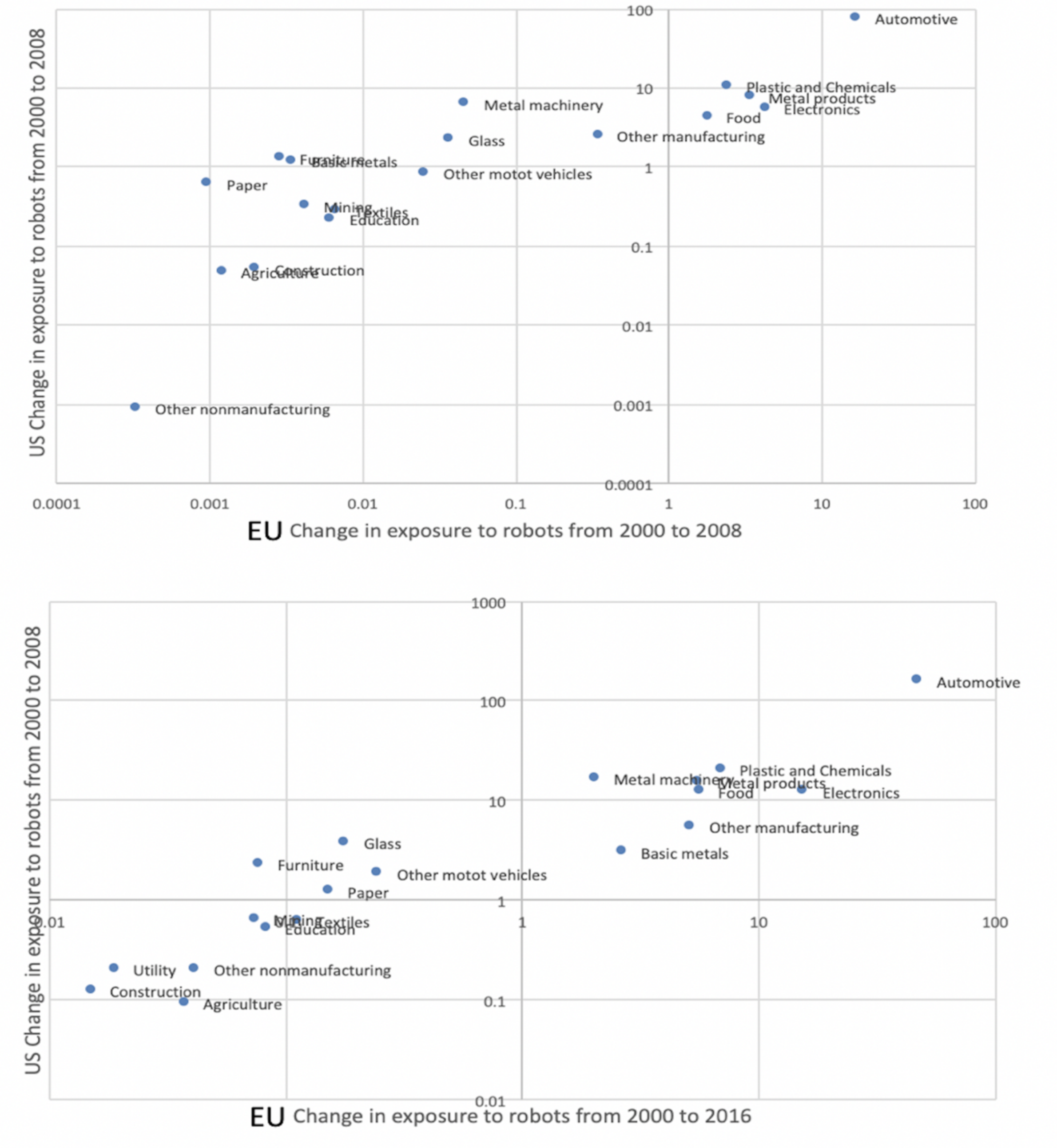
Table A4-3. Full baseline regression results of robot exposure and mortality under 2SLS estimation

	IV estimates for the effect of robot exposure on mortality caused by drug, alcohol anf other factors with fixed effects					
	DRUG	cDRUG	ALCOHOL	cALCOHOL	OTHER	cOTHER
U.S. robot exposure	1268.7	3049.3**	1355.2**	1171.8*	-75.52	11029.4***
	(1.31)	(2.70)	(2.96)	(2.35)	(-0.10)	(4.78)
Total population	391.4***	-340.0*	254.7***	-85.73	2602.3***	-1864.1***
	(4.85)	(-2.15)	(6.25)	(-1.13)	(42.85)	(-5.79)
Working age population	4824.9***	515.9	1610.5***	388.8	1840.5***	1189.4
	(8.95)	(1.21)	(6.14)	(1.93)	(4.90)	(1.56)
Black population	-2029.1***	-1399.2*	-1675.5***	-143.5	-8044.1***	-329.9
	(-4.49)	(-2.19)	(-7.26)	(-0.48)	(-25.74)	(-0.27)
Hispanics population	-1145.2***	-128.2	-149.6***	-56.51	-1313.9***	-513.7***
	(18.89)	(-1.60)	(-4.97)	(-1.48)	(-33.11)	(-3.49)
Imports from China to the U.S.	-0.00952	-0.00432	0.00128	0.00182	-0.00559	0.0122
	(-0.67)	(-0.24)	(0.13)	(0.16)	(-0.69)	(0.47)
Employment of construction industry	-455.9	-780.7	489.8**	463.5	5996.2***	-2795.6**
	(-1.16)	(-1.55)	(2.59)	(1.85)	(-4.07)	(-2.91)
Employment of manufacturing industry	1612.7	2363.5*	1372.4**	930.1*	-798.1***	9905.7***
	(1.85)	(2.39)	(3.24)	(2.06)	(-7.68)	(5.28)
Employment of non-tradable industry	232.2	-103.3	-5.399	-202.4*	-5.820**	-979.7**
	(1.65)	(-0.63)	(-0.08)	(-2.53)	(-2.96)	(-2.93)
Share of adults with less than a high school diploma	-15.45**	-27.54***	-4.008	-10.44*	0.259	-11.85
	(-3.00)	(-3.57)	(-1.28)	(-2.34)	(0.13)	(-1.56)
Share of adults with a high school diploma	-19.33***	-24.15**	-3.703	-7.605	-5.361*	-10.11
	(-3.63)	(-3.15)	(-1.24)	(-1.81)	(-2.23)	(-1.33)
Share of adults with a bachelor's degree or higher	-21.40***	-15.56*	-6.772*	-6.051	-0.725***	-8.263
	(-3.86)	(-2.05)	(-2.24)	(-1.52)	(-5.09)	(-0.96)
Real gross domestic product	-1.077***	4.304***	-0.444***	1.082	-2015.3***	13.69***
	(-5.65)	(3.41)	(-4.96)	(1.84)	(-4.67)	(5.37)
Income per capital	-5384.5***	-3879.9*	-875.7	-1167.8	-2015.7***	-2867.1
	(-4.42)	(-2.05)	(-1.18)	(-1.06)	(-4.67)	(-1.85)
Time fixed effect and commuting zone's fixed effect	✔	✔	✔	✔	✔	✔
Observations	2150	1832	1571	1519	3763	3441
Within R-squared	0.662	0.0842	0.9389	0.0702	0.7299	0.0867

Notes: The coefficients with *** are significant at the 0.1 percent confidence level ($p<0.001$); with ** are significant at the 1 percent confidence level($p<0.01$); and with * are significant at the 5 percent confidence level($p<0.05$).Exogenous instruments in panel B are the robot exposure of eight European countries.

The following figure shows the scatter plot between the U.S. robot exposure and EU robot exposure. The top panel presents the change between 2000 to 2008 and the bottom panel presents the change between 2000 to 2016. Each blue dot represents one industry and 19 industries in total. The y-axis is the change in U.S. robot exposure and the x-axis shows the change in EU robot exposure.

Figure A4-1. Scatter plots between the U.S. robot exposure and EU robot exposure in industry level



Notes: Both axis are in logarithmic scale. Data sources: International Federation of Robotics (IFR) and KLEMS.

The last figure shows the correlation between U.S. robot exposure and EU robot exposure between two different periods.

Figure A4-2. Correlation of changes in exposure of robots in industry level between US and EU

Correlation	US exposure from 2000 to 2008	US exposure from 2000 to 2016
EU exposure from 2000 to 2008	0.973	
EU exposure from 2000 to 2016		0.963

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Chapter 5

Summary of Conclusions

This thesis has evaluated the empirical evidence provided by three separate papers to detect how technological changes can affect the economy. The first paper examines whether AI, one of the more common technologies in recent years, can become the next general-purpose technology that can have a long-term effect on the global economy. The AI related patents from the U.S. patent office between 1990 and 2014 are used to measure the development of AI. These patents are divided into three categories, namely robotics, logistics systems, and learning systems. This paper finds as the stock and growth rate of AI patents in logistic systems and deep learning is higher than robotics, suggesting that the development trend of AI is learning ability to serve as a general-purpose technology, but not automation-oriented applications. Ironically, AI has been more widely utilised in the chemical and medical sectors compared to the computer science, electronics, and automotive sectors, which are traditionally seen as sectors where AI is more commonly used. These findings support the notion that AI has the potential to become a general-purpose technology as it has been extensively used in different sectors. Due to the unavailability of AI data, this thesis uses robots to replace AI to expand on the existing research.

In the second paper, the relationship between the use of industrial robots and election outcomes is investigated. The voting outcome of the presidential election and congressional election in the United States from 2000 to 2016 is used to represent the political stability in the US. The empirical research is conducted at the commuting zone level and the robot usage in European countries is used as the instrument of U.S. robot usage to deal with endogeneity. The International Federation of Robotics (IFR) provides the data of industrial robots as the only available data source. In terms of the U.S. presidential election, the increase in robot exposure is inversely proportional to the number of votes cast for the Democratic Party. That indicates that robot usage has a negative effect on the total votes of Democrats in the presidential election. In terms of the U.S. congressional election, higher robot exposure is associated with higher total votes of the Republican Party. These findings prove the correlation between industrial robots and voting outcomes in the United States. Although the effects of robot exposure vary in different types of elections and election periods, the data supports the notion that they have an impact on election results. The leader of the party may determine the right level of robotic exposure to fuel their interests. If the candidate shows willingness to protect employment in their campaign declaration, that party may receive more votes.

Finally, the third paper explored the effect of industrial robots on the mental health of workers. The data suggests that growing distress leads to increasing DSA deaths, including mortality due to drug poisoning, alcoholic liver diseases, and suicide. Therefore, the third paper uses fatalities caused by drug, alcohol and other factors of working age population (20-59 years) from the U.S. Centres for Disease Control and Prevention to measure the change in mental health condition of the labour market. The main finding is that higher usage of industrial robots is associated with higher number of fatalities caused by drug, alcohol, and all other factors. In other words, increasing robot usage leads to the of deterioration of workers' mental health in the United States. The possible explanation is the rapid development of industrial robots worsens the working environment and workers have growing mental pressures to work harder due to the risk of being replaced by robots and being subjected to decreased wages. Workers may take some extreme actions that will harm their health to reduce pressure, such consuming drugs and drinking alcohol. Thus, fatalities caused by drug and alcohol will increase. In addition, people may have less health expenditure due to less disposable income, thus worse health condition and rising mortality could be induced by other factors.

5.1 Policy implications

Based on the empirical data in the aforementioned papers, we provide several policy suggestions for policymakers when they are faced with the decision to implement new technologies.

1 Paper in chapter 2 finds that AI has the potential to become the next general-purpose technology, which means it will affect various industries and jobs in the future. The level and type of effects from AI may vary in different sectors and industries. According to findings in chapter 2, some sectors may develop and grow rapidly, such as chemical and medical sectors, thereby requiring more workers. Policy makers may need help workers in vulnerable sectors that have big share of routine jobs to face the challenge from AI and to receive more policy benefits. For example, providing unemployment compensation.

2 When AI is widely adopted and used for general purpose, we need to question whether we are prepared for that change. The labour market may experience a big change in what is expected from workers. Some skills of the workforce may become obsolete as those skills can be learned and applied by AI. Chapter 2 finds the new application sector of AI are medical and chemical sectors suggests, new skills may be required in these sectors. Due to the varying skills required, the education system may need to be restructured to become more adaptable to the changing demands from the labour market.

3 Chapter 2 finds different sectors receive different effects from AI development, either positive or negative. Companies in different sectors will also need to prepare for the changes

that AI, when broadly adopted, could bring to the way they operate. They would have to balance their strategic and profit maximisation objectives to evaluate the level of technological intervention they would implement in order to keep their competitive edge and survive in the market.

4 Chapter 3 finds the usage of industrial robots can significantly affect the election outcomes of presidential elections and congressional elections in the United States. Therefore, the incumbent party possibly should be careful when adopting new technologies to maintain political stability and avoid social unrest. In order to strengthen the political system, policymakers may need to mitigate negative effects from robots and new technologies by protecting the welfare of vulnerable people by providing more supports from transfers, health service and public financial help. Political leaders could promise the public that they will monitor the adoption of robots and new technologies and apply these technologies gradually. The government could also provide courses to help workers learn new skills.

5 Chapter 4 finds the mental health of workers deteriorates when robot usage increases in the United States. Companies may need to consider the mental health of their workers if they want to expand the use of new technologies. Companies could invite mental health professionals to provide counselling to their workers regularly. Companies could also try to understand and monitor the mental health of workers using surveys, and then provide corresponding support to workers. As previously discussed, policymakers should consider the possible transmission channels between robots and mental health. Workers are afraid of future decreasing income. Thus, policymakers could make regulations related to minimum wage. For workers that have higher risk of being replaced by robots and new technologies, they could provide better assurances for them if they experience unemployment. They could also increase the health expenditure to improve the general health of workers. More approaches that deal with increasing mental problems caused by robots and new technologies could come from more possible transmission channels that will be explored in future research.

5.2 Further study

Due to the lack of data on AI, this thesis extrapolates on existing data on the effect of AI on the economy to evaluate the impact of industrial robots on voting outcomes and mental health. With advancements in AI, the data may become available in the future which will allow further empirical studies to explore the effect of AI on the voting behaviour and mental health of workers to be conducted. It is interesting to compare the effect of AI and the effect of industrial robots on the variables evaluated in this study. If they show the same results on voting outcomes and mental health, we may able to make a general conclusion on emerging technologies.

Furthermore, this thesis narrows down the economic impact of technological changes to specific economic indicators, like elections and mental health. There still exists a lot of space to explore how new technologies impact company operations and life. As discussed in the policy implications section, technological change may affect the structure of our education due to the changes in skillsets required of the labour market. The demand of low-skilled jobs, middle-skilled jobs and high-skilled jobs in the labour market may significantly change. Therefore, it is worthwhile to investigate whether the number of people receiving differing levels of education changes as well.

In addition, the three papers evaluated in this thesis only discuss the case in the United States, which is one of the most developed countries with the most advanced technologies in the world. Future research could focus on other developed countries around the world, such as European countries, to assess whether technological changes show the same effect on elections and mental health as the United States. It would also be interesting to investigate the effect of new technologies in developing countries. Further investigation could compare the differences between the impacts that technology has on both developing and developed countries. The difficulty may be how to find appropriate data and identification strategy.

Finally, future studies could continue in the same direction as this thesis to fill in the gaps where this research lacks empirical evidence of the transmission channel between robots and mental health in the United States. Possible transmission channels have been discussed in the main text. The difficulty remains that data representing the fear caused by a lack of job security, worries of the general economic situation, and increasing work pressures, are lacking.